RED HOT AMERICAN SUMMER: EXTREME HEAT AND PHYSICAL ACTIVITY OF ADULTS

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RED HOT AMERICAN SUMMER: EXTREME HEAT AND PHYSICAL ACTIVITY OF ADULTS

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To Darshan

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS AND ABBREVIATIONS

3HEAT	Hazards SEES: Enhancing Emergency Preparedness for Critical Infrastructure Failure during Extreme Heat Events
ACSM	American College of Sports Medicine
AIC	Akaike information criterion
AQI	Air quality index
ATL	Atlanta
BIC	Bayesian information criterion
CARS	Child Activity Rating Scale
CEPA	California Environmental Protection Agency
DBH	Diameter at breast height
DET	Detroit
DNR	Department of Natural Resources
EHI	Exertional heat illness
GIS	Geographic information system
GPS	Global positioning system
HI	Heat index
HIA	Health impact assessment
LAUSD	Los Angeles Unified School District
NORA	New Orleans Redevelopment Authority
NSF	National Science Foundation
NWS	National Weather Service

RCP	Representative concentration pathway
RH	Relative humidity
SRRS	Service records retention system
SPSS	Statistical package for the social sciences
T	Temperature
TAD	Time activity diary
Td	Dewpoint
UHI	Urban heat island
US	United States
USAF	US Air Force
WBAN	Weather Bureau Army Navy
WBGT	Wet bulb globe temperature
WFO	Weather forecast office

SUMMARY

This dissertation investigates the relationship between extreme summer heat and outdoor, indoor, and total (i.e., outdoor + indoor) physical activity levels of US adults. With the lack of physical activity across the US, public health practitioners and city planners are making concerted efforts to promote physical activity through formal interventions and the design of spaces, respectively. To inform physical activity interventions, researchers examine which factors associate with physical activity, one of which is temperature. The majority of studies exhibit a significant positive association between temperature and physical activity, yet no studies examine exceptionally hot summer days, which disproportionately impact cities and are set to become more prevalent in the future. This dissertation tests three novel questions: 1) how do hot days associate with outdoor, indoor, and total physical activity; 2) how do hot days influence the effect of built environment factors on outdoor physical activity; and 3) how do heat waves – consecutive hot days – associate with outdoor, indoor, and total physical activity?

This work made use of self-reported physical activity and demographic data collected during summer 2016 for a National Science Foundation project (NSF award number: 1520803). The study sample included a spatial and demographic mix of ~50 adults per study city (i.e., Atlanta, Detroit, and Phoenix). Heat was measured as both hot days and heat waves (i.e., two or more consecutive hot days), utilizing air temperature and relative humidity data collected at each city's major airport. The examined built environment factors (i.e., density, safety, trees, hilliness, connectivity, access to parks, and access to shops + services) were primarily collected from government sources and calculated within

an 800m Euclidean distance of each study participant's home address. Separate two-level growth curve models were run for each research question, version of the dependent variable (i.e., Any Activity and Recommended Activity), and location of physical activity (i.e., outdoor, indoor, and total).

Multilevel modeling predicted that 1) hot days do not exhibit a significant association with indoor, outdoor, or total physical activity; 2) hot days do not significantly influence the effect of built environment factors on outdoor physical activity; and 3) heat waves do not exhibit a significant association with outdoor, indoor, or total physical activity. These findings refute the study hypotheses that extreme summer heat would decrease outdoor and total physical activity, while shifting physical activity to indoor, thermally comfortable environments. With high temperatures potentially not serving as a barrier to physical activity, cities should allocate resources to reducing the risk of exertional heat illness, an adverse health event expected to become more frequent with physical activity promotion and climate change.

CHAPTER 1. INTRODUCTION

1.1 Context

In recent years, the United States has struggled to reach the levels of physical activity recommended in the 2008 Physical Activity Guidelines for Americans, the current national standard developed by the US Department of Health and Human Services. These federally-prescribed guidelines are based on findings of a graded inverse association between physical activity and several chronic diseases (i.e., increases in physical activity decrease disease risk), with a larger difference in the degrees of risk between the least and most active individuals. The guidelines comprise distinct recommendations for six subgroups of the US population: children and adolescents, adults, older adults, women during pregnancy and the postpartum period, adults with disabilities, and people with chronic medical conditions (US Department of Health and Human Services 2008).

For adults – the most highly populated age range in the US – to reap substantial health benefits, the physical activity guidelines call for at least 150 minutes of moderate-intensity, or 75 minutes of vigorous-intensity aerobic physical activity, or an equivalent combination of moderate- and vigorous-intensity aerobic activity, per week. In addition, the guidelines call for adults to participate in two or more days a week of muscle-strengthening activities. Yet according to self-reported physical activity data from 2016, just about half of all US adults met the recommendations for aerobic physical activity, and about one in five adults met the recommendations for both aerobic and muscle-strengthening activity (US Centers for Disease Control and Prevention 2017).

While US adults are physically inactive as a whole, stark differences in activity exist among various demographic groups. Regarding biological characteristics, the US Centers for Disease Control and Prevention (2014) found men and younger adults to be more likely than women and older adults to meet 2008 physical activity guidelines for aerobic activity, respectively. White adults (23%) were more likely than both African American adults (18%) and Hispanic adults (16%) to meet the guidelines for aerobic and muscle-strengthening activity. In terms of lifestyle, adults with more education and adults whose family income was above the poverty level were more likely to meet guidelines for aerobic activity. Regionally, those living in the South US were less likely to be physically active than those living in the West, Northeast and Midwest US.

This lack of physical activity among adults has serious public health implications: Medical professionals have identified physical inactivity as a risk factor for a host of chronic diseases. Physical activity is a component of weight management that combats obesity through 1) prevention of weight gain, 2) weight loss, and 3) prevention of weight regain after weight loss (Donnelly et al. 2009). From 2011-2014, over a third of US adults were considered obese, which carries an annual medical cost of $147 billion. In comparison, medical costs for the obese average $1,429 more per year than those of normal weight. Obesity-related conditions include heart disease, stroke, type 2 diabetes, and certain types of cancer, some of the leading causes of preventable death (US Centers for Disease Control and Prevention 2018a).

Along with reducing the risk of chronic disease, physical activity has a positive effect on mental health. Evidence shows that moderate regular exercise is effective in reducing clinical depression and anxiety, while improving physical self-perception, selfesteem, and mood (White et al. 2017). Any level of physical activity, including low levels of 10-29 minutes a day, could prevent the onset of depression (Mammen and Faulkner 2013).

If inactive individuals were to become active, disease could be averted and life expectancy could be gained. Worldwide, physical inactivity causes six percent of the burden of disease from coronary heart disease, seven percent of type 2 diabetes, 10 percent of breast cancer, and 10 percent of colon cancer (Lee et al. 2012). The American Heart Association includes physical activity as one of seven cardiovascular health metrics in its Life's Simple 7 modifiable behaviors. Engaging in recommended levels of physical activity per week associates with a 15 percent decrease in the risk of all causes of death and a 23 percent decrease in the risk of death from cardiovascular disease (Yang et al. 2012).

With a large proportion of physically inactive adults in the US and the consequential morbidity and mortality (i.e., illness and death), the public health community over the past couple decades has been investigating which factors associate with physical activity levels to inform physical activity interventions. Recently, physical activity researchers have focused their attention on how different characteristics of the environment correlate with physical activity. Temperature is one such factor, with the majority of published studies finding individuals to be more active during summer over other seasons and a positive correlation between outdoor temperatures and outdoor physical activity (Chan and Ryan 2009, Tucker and Gilliland 2007). But the few studies assessing physical activity levels in hot and humid climates tell a different story: An increase in outdoor temperature past a certain point is associated with a decrease in physical activity

(Baranowski et al. 1993, Henry, Lightowler, and Al-Hourani 2004, Obradovich and Fowler 2017).

Whether elevated temperatures exhibit a significant or insignificant association with physical activity, humans are at risk of heat-related illness when participating in physical activity and/or subjected to hot and humid environments: In the US, extreme heat leads to more deaths each year than all other natural disasters (e.g., earthquakes, hurricanes, tornadoes, and floods) combined (Luber and McGeehin 2008). When participating in physical activity in hot and humid environments, individuals are at risk for exertional heat stroke, one of the leading causes of death in athletes.

Since 1975, the number of deaths from exertional heat stroke in the US has doubled, with more reported deaths from exertional heat stroke from 2005-2009 than any five-year period in the preceding 30 years (Nichols 2014). At the 2015 Savannah Marathon, a 35-year old man died from the unseasonably warm conditions, which reached 84˚F during the November event. Race officials reported that about two thousand runners (i.e., 10% of all race competitors) were treated for, or hospitalized with, heat-related illnesses, and more than one thousand runners were forced by officials to cut their race short due to the extreme weather (Savannah College of Art and Design 2015).

Based on past and future climate trends, both athletes and non-athletes are expected to have increased exposure to hot conditions moving forward, and therefore increased vulnerability to heat-related illness. Since 1895, US average temperatures have increased 1.3-1.9°F (Melillo, Richmond, and Yohe 2014), and across the globe, the hottest 24 years have all occurred since 1990 (Figure 1). The last decade was the warmest ever recorded in the US, and Climatologists attest that this warming is a product of greenhouse gas emissions, with the burning of fossil fuels from industrial practices equating to 75-80% of emissions and deforestation constituting the remaining emissions (Morgan, Maretti, and Volpi 2005). Consequently, warming has increased the rate of heat-related deaths between 1995-2015 (Leon and Bouchama 2015).

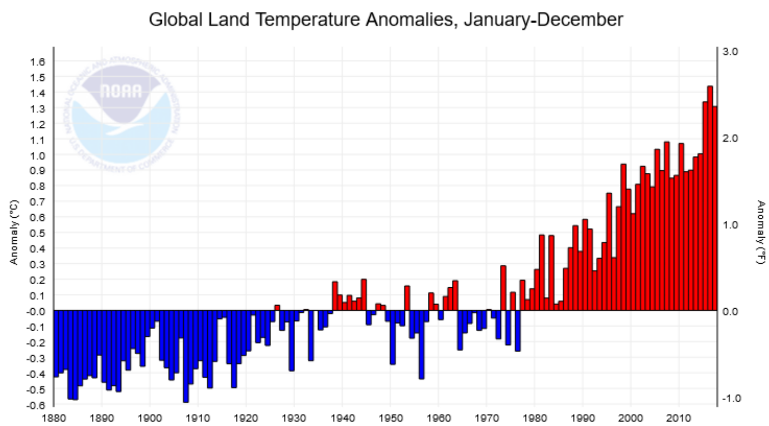

Figure 1. Global annual land temperature anomalies (1880-2017) with respect to the 20th century average.

Source: US National Oceanic and Atmospheric Administration (2018a)

The climate literature indicates future global warming will surpass that experienced in the last century. The most recent climate models include scenarios called Representative Concentration Pathways (RCPs), which show projected global warming under different greenhouse gas concentration trajectories. The lowest concentration pathway, RCP2.6, assumes immediate and rapid reductions in emissions and would result in 2.5°F of warming by 2100. The highest concentration pathway, RCP8.5, assumes very high greenhouse gas emissions and would warm the earth between 8-11°F by 2100 (Pachauri et al. 2014). In addition to rising temperatures, extended periods of high temperatures, called heat waves, are projected to increase in intensity, duration, and frequency over time (Gao et al. 2012).

In addition to warming induced by anthropogenic greenhouse gas emissions, cities are in danger of heat-related illness because of the urban heat island effect – the phenomenon in which cities experience temperatures warmer than surrounding rural areas due to changes to the land surface and to waste heat from human activities. Along with heat islands, cities are attracting a disproportionate amount of the world population: The turn of the 21st century marked the first time in history that more people lived in cities than rural areas, with projections estimating two-thirds of the world population will live in cities by 2050 (Buhaug & Urdal, 2013). In conclusion, elevated urban temperatures and increases in global temperatures, heat waves, and urban population suggest cities may be the perfect storm for heat-related illness, and potentially physical inactivity and its associated diseases, amongst the most people.

1.2 Study Purpose

The principal objective of this study is to understand how hot summer days influence outdoor, indoor, and total physical activity levels of adults. Past research has identified temperature as a significant correlate of physical activity, and this study aims to add to the evidence of a temperature-physical activity relationship. This work is novel and especially appropriate for the current and future climate by examining the physical activity correlate of temperature as exceptionally hot summer days, which have yet to be investigated and are projected to be increasingly common. This study focuses on physical activity in urban areas, because traditional development patterns in cities induce warmer temperatures than in surrounding rural areas.

Learning whether extreme heat has a negative, positive, or insignificant association with physical activity can improve comprehension of how individuals decide to interact with hot ambient environments, and ultimately better prepare cities for combatting the physical inactivity crisis. The findings from this study are intended to improve the status quo in three ways. Study results can bring about change to US weather reporting, which in current form does not place consistent emphasis on the temperature-physical activity relationship. Second, this work can assist public health practitioners in designing better informed strategies for physical activity promotion by revealing if heat acts as a deterrent or attractant for physical activity, and whether behavior puts individuals at risk for heat-related health issues. Lastly, the findings from this work can help city planners, architects, and designers create spaces that encourage physical activity while moderating heat.

CHAPTER 2. LITERATURE REVIEW

2.1 Introduction

The literature review is organized into several parts that, in aggregate, inform the development of the study research questions and design. The review begins with an overview of the health behavior models that are most commonly applied by public health practitioners for physical activity interventions. Based on the Ecological Model of four domains of active living, the review overviews different categories of correlates of physical activity, beginning with the relationship between temperature and physical activity. Following the correlate of temperature, the review discusses which factors of the built environment, in terms of both built environment characteristics and access to behavior settings, associate with physical activity – a category of correlates with direct connection to city planners. After summarizing the correlates of physical activity of interest to this work, the review shifts to the relationship of physical activity and heat to health, by first explaining the physiology of thermoregulation in humans, followed by which factors increase one's risk for heat-related illness and which factors contribute to urban areas being warmer than surrounding rural areas. Lastly, this section concludes with an overview of the three main contributions of this work and the position of these contributions within the text.

2.2 Health Behavior Models for Physical Activity

2.2.1 Traditional Models

In the 1970's and 80's, public health professionals conducted interventions to change health behavior without the use of theory to inform their strategies. These early attempts at health promotion emphasized individuals' behaviors as correlates of physical activity over the broader environmental correlates. Professionals had seen their role as working at one level of intervention, not realizing that multiple interventions at multiple levels are often needed to elicit behavior change. In more recent years, public health practitioners have adopted models to inform behavior change interventions, with the physical activity and health behavior field testing and widely adopting four models: the social cognitive models of Theory of Planned Behavior, Social Cognitive Theory, and Self-Determination Theory; and the stage-based approach called the Transtheoretical Model (Buchan et al. 2012).

The Theory of Planned Behavior states the chief determinant of behavior is behavioral intention to participate in that activity, and the direct determinants of one's behavioral intention are their attitude towards performing the behavior, their subjective norm associated with that behavior, and their perceived control over the behavior (Glanz, Rimer, and Viswanath 2008). Under this theory, an individual will engage in physical activity if they positively evaluate the behavior, believe others will join them in activity, and the activity is under their control (Buchan et al. 2012). To test the Theory of Planned Behavior, Plotnikoff et al. (2011) found the theory explained 59% and 43% of the variance for intention to participate in physical activity and physical activity behavior, respectively, among Canadian adolescents – results that corroborate with other physical activity studies adopting the Theory of Planned Behavior (Chevance et al. 2017, Downs and Hausenblas 2005, Hagger, Chatzisarantis, and Biddle 2002).

The Social Cognitive Theory posits an individual's behavior is the result of the interaction between personal, behavioral, and environmental influences. In this observational theory, individuals view others performing a behavior and the results of that behavior, potentially leading to behavior replication. The theory recognizes the role of the environment on behavior, specifically on an individual's ability to "alter and construct environments to suit purposes they devise for themselves" (Glanz, Rimer, and Viswanath 2008). Research finds that self-efficacy, or the confidence one has in achieving a specific outcome, and social support from family and friends are key variables shown to predict those individuals who will engage in physical activity (Dishman et al. 2017, Mama et al. 2017).

Self-Determination Theory is based on human motivation, focusing on the processes through which an individual acquires the motivation for initiating and maintaining health-related behaviors. The theory posits three psychological needs that must be satisfied for an individual to become active: autonomy, competence, and relatedness. Autonomy refers to being the source of one's own behavior; competence refers to feeling effective in one's social environment; and relatedness refers to feeling connected to others and the community (Buchan et al. 2012). A systematic review of Self-Determination Theory and physical activity studies found both autonomous forms of motivation and perceived exercise competence to consistently positively associate with exercise behavior (Teixeira et al. 2012).

As an alternative to social cognitive models, the Transtheoretical Model differs from other behavioral theories by incorporating a temporal dimension, allowing change to take place over time. The cyclical process of the Transtheoretical Model includes six stages of change: precontemplation, contemplation, preparation, action, maintenance, and termination. Regarding the first and last stages, precontemplation refers to the stage at which an individual does not intend to act in the near term, while termination refers to the stage at which an individual has zero temptation and complete self-efficacy. To progress through the stages of change, individuals practice 10 processes of change including consciousness raising, self-liberation, and helping relationships (Glanz, Rimer, and Viswanath 2008). From a meta-analysis, Romain et al. (2018) found Transtheoretical Model-based interventions significantly improved physical activity behavior in adults.

2.2.2 Emerging Theory: The Ecological Model

The aforementioned, traditional behavioral theories do not focus on all potential causes of poor health, which risks missing opportunities to improve health (McKinlay and Marceau 2000). Since behavior change is a complex and multifaceted phenomenon with multiple levels of influence (Buchan et al. 2012), a model needs to incorporate all downstream and upstream determinants of behavior change; the Ecological Model aims for such comprehensiveness. The model recognizes that there are multiple influences across multiple levels on specific health behaviors, and that these influences on behaviors interact across these different levels. Considering all determinants results in effective multi-level interventions for changing behavior (Glanz, Rimer, and Viswanath 2008).

Ecological Models are behavior-specific such that models for smoking behavior and physical activity will have different sets of influences at each level. Conceptually, Ecological Models comprise a set of concentric rings, centering on the individual and moving outwards to different types of environments. Figure 2 depicts an Ecological Model of four domains of active living developed by Sallis et al. (2006). This model groups factors influencing physical activity behavior into seven categories: Intrapersonal, Perceived Environment, Behavior Settings, Policy Environment, Social Cultural Environment, Information Environment, and Natural Environment.

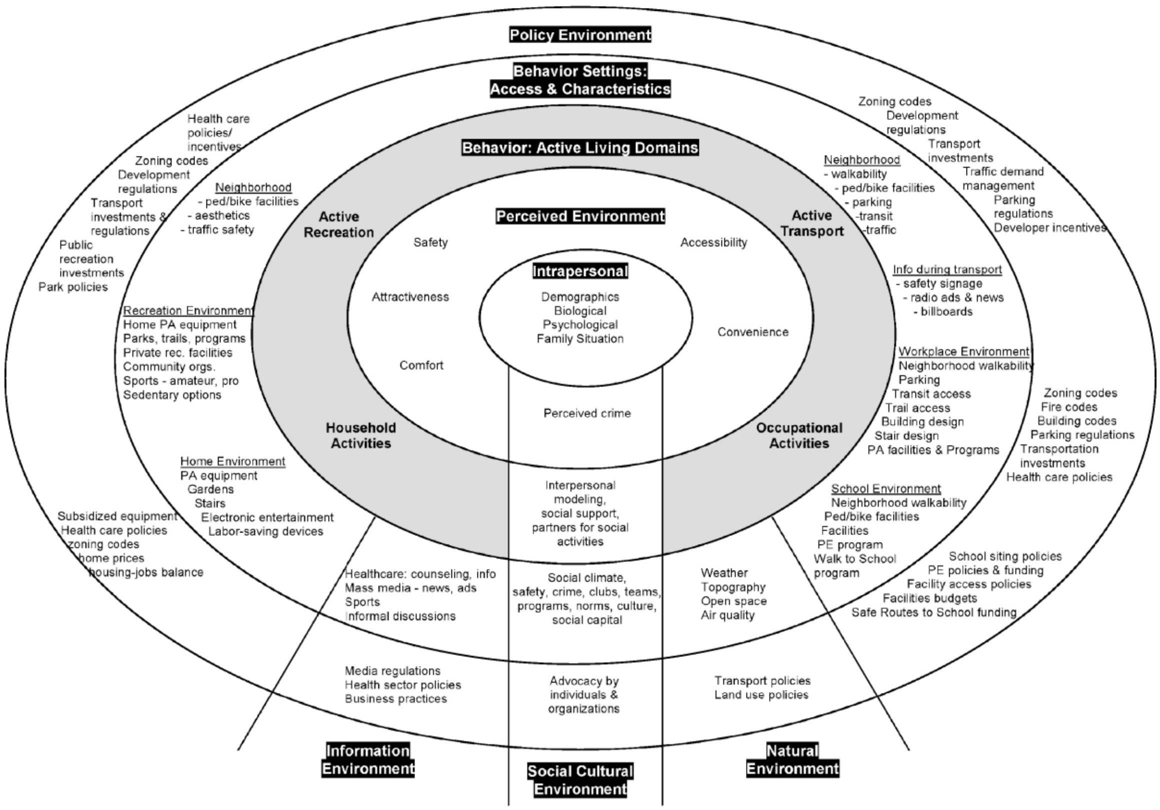

Figure 2. Ecological Model of four domains of active living.

Source: Sallis et al. (2006)

The model shows physical activity occurs in four domains with a range of factors at multiple levels that may influence physical activity behavior. The inner circle and first ring, or the Intrapersonal and Perceived Environment levels, are more central than the ring representing active living domains because the factors within these levels are based on personal characteristics. Within the Intrapersonal level, an example of a biological factor is age: Older adults are less likely to meet national physical activity guidelines than younger adults (US Centers for Disease Control and Prevention 2014). The levels of Information Environment, Social Cultural Environment, and Natural Environment cut across other levels, e.g., the factor of perceived crime appears in both the levels of Social Cultural Environment and Perceived Environment. Pulling from systematic reviews of physical activity correlates in low- and middle-income countries, Bauman et al. (2012) found research has disproportionately reported correlates in the demographical and biological level, with less focus on other levels (Figure 3).

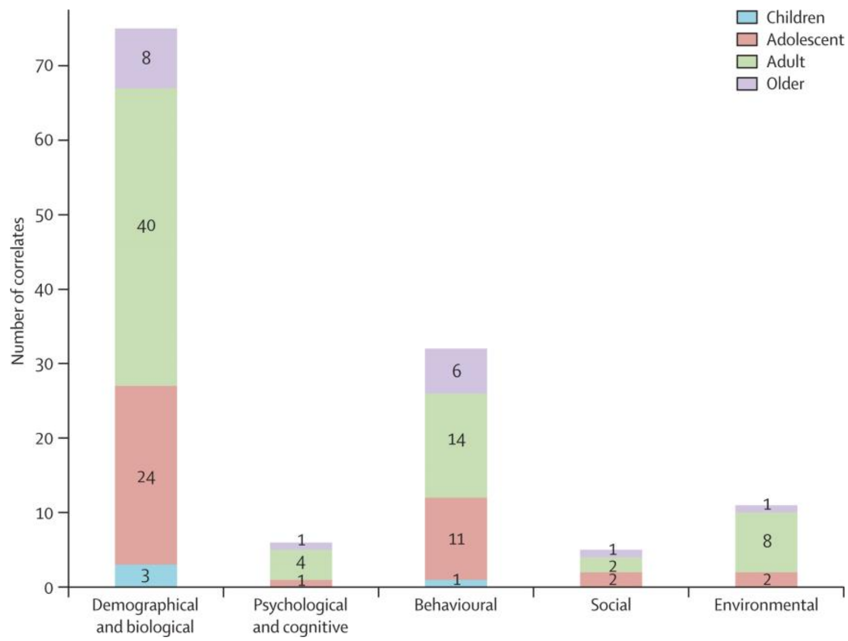

Figure 3. Correlates of physical activity identified in low- and middle-income countries.

Source: Bauman et al. (2012)

Along with having a range of factors at multiple levels, Ecological Models of physical activity comprise multiple active living domains (i.e., active recreation, active transport, household activities, and occupational activities) because each domain may exhibit a different response to a factor within a level of the model. For example, Van Holle et al. (2012) found the factors of walkability, access to shops + services + work, and degree of urbanization had significant positive associations with transportation physical activity, while each of these factors exhibited no relation to recreational physical activity. However, some factors specific to one activity domain may translate to another domain. Two separate meta-analyses found land use mix and walkability to exhibit significant positive associations ($p < 0.05$) with both active travel and leisure-time physical activity in older adults (Cerin et al. 2017, Van Cauwenberg et al. 2018).

Ecological Models draw the central conclusion that significant changes in health behavior require a combination of both individual- and environmental-level interventions (Glanz, Rimer, and Viswanath 2008), an aspect missing from other theories of health behavior. Educating individuals about outdoor activities to reach national guidelines for aerobic activity without having suitable environmental conditions like safe sidewalks to practice these activities may be insufficient to change behavior. Conversely, environmental changes may not change behavior without changes at the individual level. Constructing more access points to a nearby bike trail may not improve ridership if individuals are unaware of the environmental change, unable to ride a bike, and/or perceive crime to be high on the trail. In summation, Ecological Models provide a holistic approach for directing research and guiding physical activity interventions with a flexible, focused framework constructed to affect long-term behavior change.

2.3 The Temperature-Physical Activity Relationship

2.3.1 Link between Weather and Behavior

Within the Ecological Model of four domains of active living developed by Sallis et al. (2006), Weather is a factor found in both the Natural Environment and Behavior Settings levels that has garnered the attention of physical activity researchers (Figure 2). The term “weather” refers to short-term changes in the atmosphere, changes that can take place at multiple temporal scales such as minute-to-minute and season-to-season. Weather includes multiple elements, e.g., precipitation, temperature, and humidity, all of which can potentially affect an individual’s activity level. Regions around the world exhibit different average daily weather over long periods of time, known as climate (National Aeronautics and Space Administration 2015).

The microclimate – the local set of atmospheric conditions of an area – has been shown to impact human behavior (Zacharias, Stathopoulos, and Wu 2001). A review of the literature reveals that individuals modify their behavior based on 1) direct exposure to the weather and/or 2) provided information on current/forecasted weather conditions. Regarding exposure, Keller et al. (2005) noted that "one must be exposed to the weather for it to affect one's psychological processes," and subsequent research found the elderly, when coping with heat, were almost entirely reactive in their actions, rather than preparing for current or future events (Wolf et al. 2009). When experiencing less than ideal weather conditions, beachgoers in Queensland, Australia, made behavioral adjustments (i.e., use of shade umbrellas, use of windbreaks, and increased frequency of swims) to create an acceptable microclimate (De Freitas 2015).

Alternatively, weather information supplied by external sources has been tied to individual planning behavior (Liu, Kostakos, and Li, 2015). Individuals glean weather information from a variety of forecast sources, of which preference has changed with rapid technological advances. Two surveys, one in 2006 and another in 2015, asked Americans about their frequency of use of different weather sources. In 2006, the forecast sources of local TV stations (36%), newspapers (24%), and cable TV stations (22%) had the highest percentages of respondents checking for weather information at least once a day (Lazo, Morss, and Demuth 2009). In 2015, Americans shifted their source preference, with smartphone applications on mobile phones (80%), friends/family (17%), and Internet sites

(9.4%) having the highest percentages of respondents checking for weather information at least once a day (Phan et al. 2018).

Research shows that when viewing a weather forecast, people do not consider all elements of a forecast to carry equal weight (Stewart et al. 2012). Among weather elements (i.e., precipitation, temperature, humidity, wind, and cloud cover), Americans perceive forecasts for precipitation and temperature as most important. Specifically, individuals are interested in the chance of precipitation and when it will occur, as well as the daily high and low temperatures (Lazo, Morss, and Demuth 2009; Phan et al. 2018).

The use of the weather forecasts depends on an individual's frequency of accessing forecasts, and his or her level of importance given to precipitation and temperature forecast information (Demuth, Lazo, and Morss 2011). When Lazo, Morss, and Demuth, (2009) asked Americans how often they used weather forecasts for certain activities, the greatest percentages of respondents replied "usually or always" for simply knowing what the weather will be like (72%), planning how to dress (55%), planning weekend activities (42%), planning travel (40%), planning to do yard work or outdoor house work (38%) and planning how to get to work or school (30%). A follow up study validated that planning for leisure activities and for work/school-related activities factored into forecast use (Demuth, Lazo, and Morss 2011).

2.3.2 Temperature as a Correlate of Physical Activity

Whether through direct exposure or forecast, the weather element of temperature can modify human behavior. This section focuses on temperature and its relation to physical activity behavior, in particular how the relationship differs based on regional climate.

Seasonal variation in physical activity can serve as a proxy for the relationship between temperature and physical activity, with two systematic reviews showing that individuals exhibit increased leisure time physical activity in summer over winter months (Chan and Ryan 2009, Tucker and Gilliland 2007). A study of Scottish adults found physical activity peaked in July with 32% of individuals reporting exercise for at least 20 minutes three or more times during the previous week, while winter associated with a drop to 23% (Uitenbroek 1993). Among older Canadians, Jones, Brandon, and Gill (2017) found average hourly physical activity values increased by ~50 accelerometer counts (9.8 m/sec^2) per minute with each subsequent month from February to April. Among young Dutch adults, Plasqui and Westerterp (2004) found physical activity levels, measured as total energy expenditure divided by sleeping metabolic rate, were higher in summer than winter (1.87 +- 0.22 vs. 1.76 +- 0.18); $p < 0.001$), with a higher difference between seasons for men than women (0.20 +- 0.14 vs. 0.05 +- 0.16; $p = 0.04$). Lastly, a study found Canadian children had increased odds of meeting physical activity guidelines in the spring (Odds ratio = 1.6, 95% confidence interval = 1.2–2.2) and summer (Odds ratio = 1.7, 95% confidence interval = 1.2–2.5) compared to the winter (Belanger et al. 2018), but seasonality in children's physical activity does not serve as a valid proxy for the relationship between temperature and physical activity because of the amount of time students spend out of school in the summer confounds the relationship.

From a review of the literature, the relationship between temperature and physical activity seems to depend on the distance an individual lives from the equator. Locations at higher latitudes in the temperate zones exhibit a positive association between temperature and physical activity. Among adults in Prince Edward Island, Canada, Chan, Ryan, and Tudor-Locke (2006) found that every 10°C increase in mean temperature correlated with a 2.9% (95% confidence interval = 0.4–5.4) increase in steps per day. Stateside, Suminski et al. (2008) examined the effect of apparent temperature, a combination term for air temperature, relative humidity, and wind, on individuals walking to school, exercising on oval tracks, and walking/jogging on sidewalks and streets in Columbus, Ohio. Through multiple regression analyses, the authors found higher apparent temperatures associated with more walkers ($\beta = 0.837$, $p = 0.001$) and joggers ($\beta = 0.643$, $p = 0.022$), in addition to longer jogging times ($\beta = 0.814$, $p = 0.007$).

Like adults, individuals both young and old exhibit a positive association between temperature and physical activity at higher latitudes. In a study of school children in New Zealand, a mean ambient temperature increase of 10°C was associated with boys taking 1,700 more weekday steps (90% confidence interval ±1,300) and 3,400 more weekend steps (90% confidence interval ±1,500), while girls took 2,300 more weekday steps (90% confidence interval ±1,000). In addition, the greatest effect of temperature on steps was in the lowest socioeconomic group: each 10°C increase associated with 4,400 more steps (90% confidence interval ±2,300) by boys and 1,400 more steps (90% confidence interval ±1,700) by girls (Duncan et al. 2008). Regarding the elderly, Klenk et al. (2012) found Germans over age 65 extended their walking duration by more than seven minutes with each 10°C increase in maximum daily temperature.

Opposed to locations in temperate zones, locations near the equator in the tropics and subtropics exhibit a negative association between temperature and physical activity once temperatures reach a certain level. In a longitudinal study of adults in Qatar, daily weather metrics had negative associations with physical activity: every one-unit increase in average outdoor temperature, relative humidity, and heat index (i.e., a combination term for temperature and relative humidity) resulted in five (± 2), two (± 0.46), and 24 (± 4) less steps taken per day. On average, participants took 12% less steps per day in the month with the least steps (August) versus the month with the most steps (December) (Al-Mohannadi et al. 2016). Even adult athletes who routinely participate in organized sport respond negatively to heat. Researchers examined how different levels of heat index affected the number of steps taken by semi-professional soccer players in Turkey, finding players covered six percent fewer meters in a game with high heat index (49 ± 1°C) over a game with moderate heat index (35 ± 1°C). The greatest effect of heat can be seen when comparing the second halves of the games, as players covered 11 percent fewer meters in the high heat index game over the moderate heat index game (Özgünen et al. 2010).

High temperatures in the tropics and subtropics also affect physical activity levels among those at both ends of the age spectrum. Togo et al. (2005) investigated the relationship between daily mean ambient temperature and ensemble-averaged step counts of elderly Japanese for over a year, finding mean ambient temperatures from -2 to 17°C led to an increase in the number of steps, while mean ambient temperatures from 17 to 29°C led to a decrease in steps (Figure 4). Furthermore, the period from June 22nd through August 21st exhibited a -0.373 correlation ($p < 0.05$) between mean ambient temperature and the number of steps, making this summer period the only period across the full study without a significant positive correlation between temperature and steps.

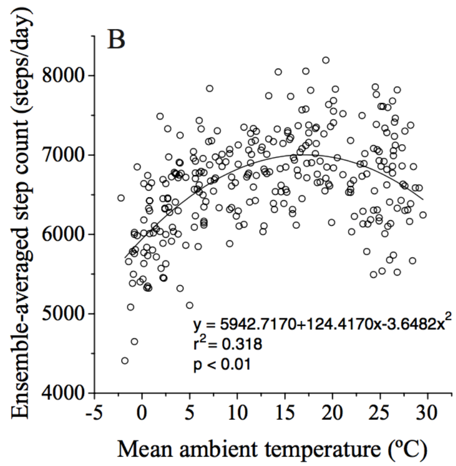

Figure 4. Relationship between mean ambient temperature and number of steps among elderly Japanese.

Source: Togo et al. (2005)

Among preschool children in Galveston, Texas, Baranowski et al. (1993) measured physical activity using the Child Activity Rating Scale (CARS), a five-level scale in which a score of one signifies ‘stationary’ and five signifies ‘fast trunk movement/strenuous.’ Across all months, the authors found that July had the lowest CARS scores for both males (2.16) and females (2.19). The authors noted that at the time of the study, the average July temperature was 29.1°C, the hottest of all months. In 2012-2013, Martins et al. (2017) measured the physical activity levels of young Brazilian adults by GT3X+ accelerometers for one week every month over the full year. The authors found the amount of physical activity throughout the year was relatively stable, with ~five percent of each day spent in moderate-to-vigorous physical activity every month. However, the average temperature ($\rho = -0.64$; $P = .007$) and humidity ($\rho = -0.68$; $P = .004$) were inversely correlated to moderate-to-vigorous physical activity in the summer.

2.4 Built Environment as a Correlate of Physical Activity

2.4.1 Defining the Built Environment

Within the Ecological Model of four domains of active living developed by Sallis et al. (2006), Behavior Settings, sandwiched between individual and policy levels, is an environmental level that represents the places where physical activity may occur. Behavior Settings, known as the Built Environment in other Ecological Models (Sallis et al. 2012, Tully et al. 2013), can be divided into characteristics of the places where physical activity may occur and access to these places. In addition, the cross-cutting levels of Information Environment, Social Cultural Environment, and Natural Environment add factors within the Behavior Settings ring in the model (Figure 2). Factors within Behavior Settings serve as essential ingredients together with individual and policy factors to create a recipe for comprehensive physical activity interventions, as interventions at one level can complement interventions at other levels.

As an alternative to the Ecological Model developed by Sallis et al. (2006), the Ecological Model of physical activity updated by Sallis et al. (2012) includes the environmental levels of the Social Cultural Environment, Built Environment, and Policy Environment, with these levels depicted as full rings, i.e., without levels cutting into other levels. The Built Environment covers the physical environment, defined as the "objective and perceived characteristics of the physical context in which people spend their time (e.g., home, neighborhood, school), including aspects of urban design (e.g., presence and structure of sidewalks), traffic density and speed, distance to and design of venues for physical activity (e.g., parks), crime, and safety" (Davison and Lawson 2006). The literature on environmental correlates of physical activity tends to follow this model of lumping manmade and natural characteristics forming the physical environment into the built environment (Humpel, Owen, and Leslie 2002, McCormack and Shiell 2011, Salvo et al. 2014). The built environment correlates of physical activity outlined in the next sections are not exhaustive; instead, the sections cover correlates that are often cited in the literature and show significant associations with physical activity.

2.4.2 Characteristics of the Built Environment

The public health literature has tested several characteristics of the built environment to reveal whether associations with physical activity exist. For one, research finds the degree of urbanization (or population density) correlates with physical activity. Although the term "urban" lacks a standard definition, the 2010 US Census defines an urban area as one that comprises a "densely settled core of census tracts and/or census blocks that meet minimum population density requirements, along with adjacent territory containing non-residential urban land uses as well as territory with low population density included to link outlying densely settled territory with the densely settled core" (US Census Bureau 2010a).

In a review of European studies examining the physical environment and physical activity, summary results showed positive associations between urbanization and the outcomes of total walking/biking and transportation biking, but a negative association between urbanization and total physical activity (Van Holle et al. 2012). A study of adults from 14 cities in 10 countries found net residential density (i.e., number of residential dwellings divided by the residential land area) was positively related to physical activity (exp[b] = 1.006, 95% confidence interval = 1.003–1.009) (Sallis et al. 2016).

Regarding the relationship between urban sprawl and physical activity, Garden and Jalaludin (2009) found a positive association between sprawl and the likelihood of inadequate physical activity (Odds ratio = 1.11, 95% confidence interval = 1.06–1.16) among Australian adults, with inadequate physical activity defined as not completing ≥150 minutes of exercise per week over five separate bouts. The authors also found a positive association between sprawl and the likelihood of not spending any time in the last week walking (Odds ratio = 1.17, 95% confidence interval = 1.09–1.25). Similarly, Rashad (2009) found sprawling areas had lower prevalence of biking among US adults, with a lower degree of urban sprawl associated with men and women increasing biking by 3.4–4.4% and 1.6–2.1% from the means, respectively.

Urban sprawl not only correlates with reduced physical activity, but also with reduced pedestrian safety. In a study examining the relationship between urban sprawl and traffic fatalities across 101 US metropolitan areas, every one percent increase in sprawl index (i.e., more compact, less sprawl) associated with a 1.47–3.56% decrease in pedestrian fatality rates ($p < 0.001$) (Ewing, Schieber, and Zegeer 2003). Pedestrian safety is a growing concern not only in sprawling areas but across development types in the US: an estimated six thousand pedestrian traffic fatalities occurred across the nation in 2016, the first year above six thousand pedestrian deaths in the preceding two decades (Governors Highway Safety Association 2017). Physical activity correlates with the level and safety of automobile traffic: a meta-analysis found adults who reported that heavy traffic was not a problem were more likely to engage in physical activity compared to those reporting heavy traffic was a problem (Odds ratio = 1.22, 95% confidence interval 1.08–1.37) (Duncan, Spence, and Mummery 2005), and studies in the United Kingdom found a significant positive association between traffic-related safety and recreational walking/biking (Foster et al. 2009, Foster, Panter, and Wareham 2011).

For safety and utility, individuals benefit from having the infrastructure available to separate their mode of movement, e.g., walking and biking, from other modes like driving. Through mixed-model regressions, Sallis et al. (2015) revealed significant positive associations between the presence of a sidewalk and walking and biking for transport for children ($t = 4.82$, $p < 0.001$), adults ($t = 3.05$, $p < 0.002$), and older adults ($t = 2.17$, $p < 0.03$) in three US cities. When older adults with mobility disabilities in King County, Washington, were interviewed about built environment barriers and facilitators to physical activity, researchers found no sidewalks, uneven sidewalks, coarse sidewalk material, and the absence of sidewalks obstructed physical activity (Rosenberg et al. 2012). Buehler and Dill (2016) reviewed the effect of bikeway networks on cycling, and found the majority of studies show a positive correlation between aspects of bikeway networks (e.g., bicycle lanes, paths, cycle tracks, traffic calming measures, and intersection treatments) and cycling levels.

Regarding natural characteristics of the built environment, significant correlates of physical activity include aesthetics, vegetation, and elevation change (or hilliness). While individuals tend to be more physically active in areas with pedestrian and bike infrastructure, an area's surroundings can influence physical activity levels too. In a systematic review of the characteristics of public open spaces that associate with visitation and physical activity of adolescents, Van Hecke et al. (2018) found that lack of cleanliness (e.g., presence of broken glass and graffiti), uneven and cracked sidewalks, and poor maintenance of facility equipment negatively associated with visitation and physical activity, while clean spaces, graffiti in designated areas, well-maintained and modern equipment, water features, and attractive vegetation positively associated with visitation and physical activity. In addition, park aesthetics – picturesque settings with trees and landscaping – have been shown to be a significant driver of park use (Veitch et al. 2017).

Vegetation is a natural environment element that may encourage physical activity for its aesthetic value and ability to improve thermal comfort. A research study in Canada showed adults who lived in the highest quartile of greenness, based on a 500m buffer, were more likely to participate in leisure-time physical activity than adults in the lowest quartile (Odds ratio = 1.34, 95% confidence interval = 1.25-1.44) (McMorris et al. 2015). Another study of Canadian adults found that the amount of vegetation along city streets exhibited a significant positive association with overall leisure-time physical activity of Canadian adults during the summer ($p < 0.01$) (Villeneuve et al. 2018). Children in California who experienced >20 minutes of daily exposure to greener spaces (> 90th percentile) engaged in almost five times the daily rate of moderate-to-vigorous physical activity of children with near zero daily exposure to greener spaces (95% confidence interval = 3.09–7.20) (Almanza et al. 2012).

The health literature purports that hilliness can have mixed correlations with physical activity. McGinn et al. (2007) found individuals were more likely to walk or participate in any transportation activity when hills were not perceived to be common in their neighborhood, yet the authors found no significant association between objective measures of hills and physical activity. Another study found slope exhibited a positive association with recreation walking (Odds ratio = 1.15, 95% confidence interval = 1.00–1.34 and a negative association with transportation walking (Odds ratio = 0.82, 95%

confidence interval = 0.68–0.98) (Lee and Moudon 2006). These results may signify that recreational walkers enjoy the views and increased exercise opportunities that come from hilly landscape, while transportation walkers are partaking in a utilitarian activity, with hilliness serving as a barrier to their commute. Research found similar results with cyclists: hilliness exhibited a negative association with transportation biking among adults (Vandenbulcke et al. 2011, Winters et al. 2010).

2.4.3 Access to Behavior Settings

The described characteristics of the built environment are only one side of Behavior Settings within the Ecological Model; individuals must also have access to these places to participate in physical activity. One chief aspect of access to a behavior setting is connectivity, defined as the "density of connections in path or road networks, and the directness of links" (Victoria Transport Policy Institute 2017). A well-connected pedestrian or road network comprises many short links and intersections with few cul-de-sacs, a structure which allows for more direct travel between destinations. The health literature indicates that connectivity may increase physical activity: the number of intersections within a census block in Portland, Oregon, positively associated with distance walked by adults ($\beta = 0.006$, $p < 0.05$), and in the metropolitan areas of San Diego and San Francisco-Oakland-San Jose, each four-way intersection within a quarter mile radius of home increased the frequency of non-work walk/bike trips by 3.2% ($p < 0.001$) (Boarnet, Greenwald, and McMillan 2008, Chatman 2009). In an investigation of the relationship between intersection density and park-based physical activity, Kaczynski et al. (2014) found study participants in the third and fourth quartiles of intersection density were more likely to engage in park-based physical activity than those in the lowest quartile (Odds ratio = 1.76–2.34, $p < 0.05$).

While connectivity allows for more efficient routes from place to place, land use that contains recreational and utilitarian destinations supplies individuals with the places to go. Urban greenspace, which includes spaces both public (e.g., parks and cemeteries) and private (e.g., private backyards and corporate campuses), benefits cities as recreational space for physical activity: In Bristol, England, individuals living > 2,250 meters from formal greenspace were 36% less likely to visit greenspace at least once a week (95% confidence interval = 0.55–0.75) and 24% less likely to achieve physical activity guidelines (95% confidence interval = 0.65–0.88) than individuals living < 830 meters from formal greenspace (Coombes, Jones, and Hillsdon 2010). Among Australian adolescents, Edwards et al. (2015) found park use for physical activity was positively associated with the presence of a skate park, walking paths, barbeques, picnic tables, public access toilets, lighting around courts and equipment, and > 25 trees ($p < 0.05$). A systematic review of US studies examining the relationship between park access and objectively measured physical activity showed mixed associations: Five studies found a statistically significant positive association between park access and physical activity, nine studies found no association, and six studies had mixed findings (Bancroft et al. 2015). For example, neighborhood park acreage within a half-mile walk was found to positively associate with physical activity ($\beta = 0.02$, $p < 0.10$) in Chicago, Illinois (Fan, Das, and Chen 2011).

Regarding utilitarian destinations, two systematic reviews and meta-analyses found strong positive associations ($p < 0.001$) between the overall access to/availability of destinations and services and 1) total physical activity of older adults and 2) total walking of older adults, respectively (Barnett et al. 2017, Cerin et al. 2017). Through mixed-model regressions, Cain et al. (2014) found both the number of nearby shops ($t = 4.82$, $p < 0.001$) and restaurant/entertainment venues ($t = 4.82$, $p < 0.001$) exhibited significant positive associations with walking and biking for transport for adults. In a study of Australian adults, each additional utilitarian destination (i.e., convenience stores, newsstands, post offices, bus stops, schools, shopping malls, and transit stations) within 1,500m of home correlated with an increase of 9.61 minutes per two weeks of walking for transport ($p < 0.05$) (McCormack, Giles-Corti, and Bulsara 2008). Another study found that distance to one's workplace was the most significant contributor to transport-related walking, with perceived proximity to work from home associated with a 15-minute increase in weekly walking ($p < 0.05$) (Cerin et al. 2007).

Evidence exists that proximity to spaces for physical activity correlates with participation in physical activity recommended by US physical activity guidelines: North Carolina residents who reported access to places for physical activity exhibited increased recommended physical activity during leisure time (Odds ratio = 2.15, 95% confidence interval = 1.23–3.77) (Huston et al. 2003). Similarly, individuals who reported the presence of nearby physical activity facilities were more likely to engage in physical activity than those not reporting nearby facilities (Odds ratio = 1.20, 95% confidence interval = 1.06–1.34) (Duncan, Spence, and Mummery 2005).

2.5 The Relationship of Physical Activity and Heat to Health

2.5.1 Physiology of Thermoregulation

In humans, thermoregulation is a set of physiological processes that continually take place to maintain the core body temperature within a few tenths of a degree of 37 °C (Worfolk 2000). The body must maintain core temperatures near this biological set point or risk heat-/cold-related illness or death. Outside of fever induced by illness, there are two major drivers of elevated core body temperature: 1) an increase in metabolic rate and 2) exposure to environmental temperatures above the biological set point (Figure 5). Physical activity causes active heat stress, as core temperatures during exercise rise with metabolic rate. Hot and humid environments cause passive heat stress, as dry heat gain from the environment outpaces the body's cooling techniques, leading to heat storage (Cramer and Jay 2016). When performing physical activity in a hot and humid environment, thermoregulation is a physiological challenge due to the multiple stressors put on the body and its cardiovascular system.

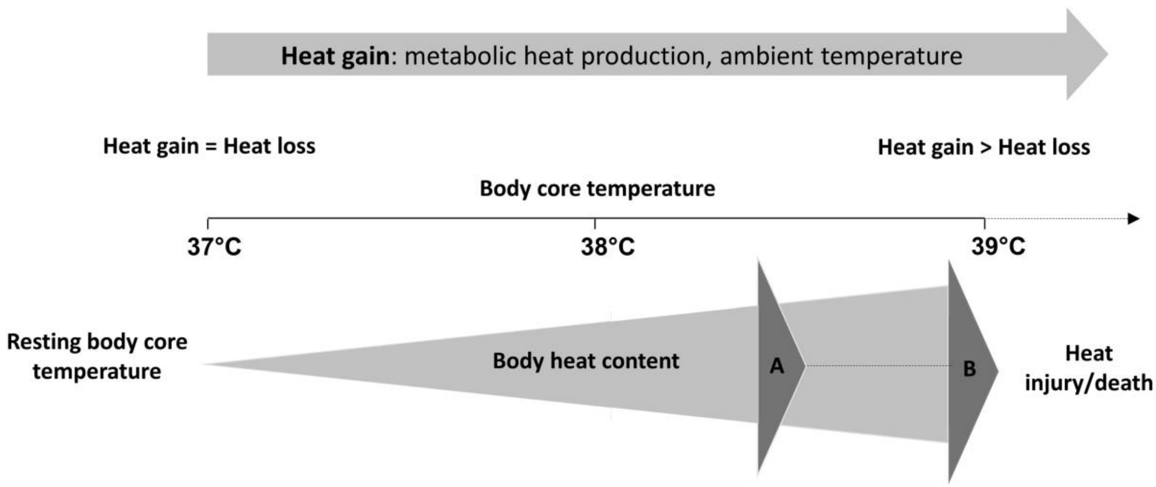

Figure 5. The human heat stress response.

Source: Yardley et al. (2013)

To reach thermal homeostasis when the core body temperature is excessively high, the body increases heat dissipation by two major mechanisms: cutaneous vasodilation (i.e., widening of blood vessels in the skin) and sweating. When the core body temperature increases due to high ambient temperatures in absence of physical activity, simultaneous renal and splanchnic vasoconstriction (i.e., narrowing of the blood vessels in the internal organs) and peripheral vasodilation occur, moving blood to the body's periphery. The increase in heart rate and cardiac output transports large volumes of blood to the skin, leading to heat dissipation by increasing convective heat transfer from the core to the periphery. Sweating, the greatest avenue of heat loss, increases with increasing core temperature, resulting in evaporative heat loss cooling the skin and increases in heat transfer from the skin's surface to the environment (Charkoudian 2016). These two thermoregulatory mechanisms of cutaneous vasodilation and sweating are linked, as cutaneous vasodilation provides the heat required for evaporation of sweat, as well as blood plasma, an essential precursor for sweat production (Smith and Johnson 2016).

The challenge of thermoregulation increases when physical activity is coupled with a hot and humid environment, as the metabolic and thermoregulatory demands compete with one another. During physical activity, active skeletal muscles demand blood to perform work. The cardiovascular system appeases the demand through increased cardiac output, the vasodilation of these exercising skeletal muscles, and the redistribution of blood flow away from other regions such as the internal organs and skin. Performing physical activity impairs thermoregulation because it leads to an initial cutaneous vasoconstriction. Physical activity delays the onset of cutaneous vasodilation by increasing the core temperature threshold for cutaneous vasodilation, which varies with the intensity of activity.

If physical activity continues under hot and humid conditions, muscle activity is prioritized over heat dissipation, i.e., physical activity serves as a brake on active cutaneous vasodilation. While skin blood flow will continue to increase with core temperatures during prolonged activity under hot and humid conditions, once the core reaches about 38°C, the internal temperatures continue to increase and skin blood flow reaches an upper limit. This compromises one of the body's mechanisms for eliminating heat: the loss of a thermal gradient from core to periphery (Johnson 2010). In conclusion, the net result of physical activity in a hot and humid environment is that the cardiovascular system prioritizes blood flow to active muscle while limiting blood flow to skin. Under these conditions, heat-related morbidity and mortality can ensue if an individual is unable to shed heat in a timely manner.

2.5.2 Heat-Related Illness and its Risk Factors

Along with potentially impeding physical activity, high temperatures can overburden the thermoregulatory process to the point of heat-related health issues. Heat illness is on a continuum from heat exhaustion to the medical emergency of heat stroke. Heat exhaustion, defined by a core body temperature between the biological set point and 40˚C (104˚F), is characterized by one or more of the following symptoms: profuse sweating, weakness, rapid breathing, muscle cramps, dizziness, nausea, and vomiting (Minnesota Department of Health 2012). If measures are not taken to reduce core body temperature, heat stroke, defined by a core body temperature ≥ 40˚C, can occur. Heat stroke is characterized by a worsening of heat exhaustion symptoms, along with central nervous system dysfunction such as delirium and coma (Glazer 2005). From 2006-2010, heat stroke was cited as the contributing cause or underlying cause of 3,332 deaths in the US (Berko 2017). In response to heat-related mortalities, the medical community has identified characteristics that increase the risk for heat-related illness, which can be divided into three groups: 1) thermoregulatory limitations, 2) behavioral/social factors, and 3) location factors.

Select population subgroups have difficulty with thermoregulation, including the elderly, children and adolescents, pregnant women, and those with chronic diseases, i.e., obesity, diabetes, and cardiovascular disease. The elderly are traditionally considered the most vulnerable population to heat due to thermoregulatory impairments, higher incidence of chronic disease, dehydration, and drug effects. Compared to younger adults, the elderly have lower tolerance to exercise heat stress and exhibit higher heart rates, lower stroke volume, lower cardiac output, higher mean skin and core temperatures, and lower sweat rates than younger adults (Casa, Clarkson, and Roberts 2005).

In children, the thermoregulatory systems are still developing, making them less heat tolerant than adults in hot conditions. Children under five years old cannot increase their cardiac output when faced with heat stress, and have a lower sweat rate and sweat rate per body surface area than adults. Furthermore, because a child's mobility and mental functioning are still developing, a child may not be able to remove him or herself from conditions of heat stress. Adolescents participating in sports may be pressured by coaching and peers to practice in extreme temperatures, which, coupled with lack of experience in these conditions and perceived invincibility can have negative health implications (Casa, Clarkson, and Roberts 2005, Falk 1998, Grubenhoff, du Ford, and Roosevelt 2007).

Pregnant women have a basal metabolic rate of 112 megajoules higher than before pregnancy (Goldberg et al. 1993). This means that a pregnant woman expends more energy at rest than a non-pregnant woman, which puts greater stress, or workload, on the cardiovascular system at baseline (rest). Obese individuals are at greater risk for heat-related illness. Adipose tissue has reduced thermal conductivity and an increased capacity to thermally insulate, so the excess fatty tissue found in obese individuals serves as a barrier to conductive heat flow, reducing the ability to respond to increasing core temperature from heat stress. In addition to obese people having lower tissue conductance than non-obese people, the obese have lower sweating rates, limiting total heat loss capacity (de Graaf, Freidig, and van Ommen 2009).

Diabetes and cardiovascular disease are associated with a reduced ability to thermoregulate (Kenny, Sigal, and McGinn 2016). Diabetics can exhibit diabetic peripheral neuropathy, i.e., nerve damage, which can be associated with partial or complete lack of sweating in some areas of the body (Charkoudian 2016). On top of nerve damage, patients with type 2 diabetes exhibit decreased cutaneous vasodilator responses when exposed to high temperatures and delayed thresholds for the onset of cutaneous vasodilation (Greaney, Kenney, and Alexander 2016). Those with cardiovascular disease have limited heat tolerance because of reduced cutaneous vasodilatory capacity at rest and during exercise (Greaney, Kenney, and Alexander 2016). Hypertensive patients exhibit higher cardiac work and skin temperatures than non-hypertensive patients, with the difference increasing further with water ingestion (Ribeiro et al. 2004).

In addition to challenges with thermoregulation, behavioral/social factors and location factors increase the risk for heat-related illness. Studies have identified correlates of heat-related illness from the 1995 Chicago Heat Wave, one of the deadliest natural disasters in US history. Chicago experienced record high temperatures for the month of July, with the Chicago Midway Airport recording maximum temperatures from July 12-16th of 97, 106, 102, 98, and 93˚F, respectively. From July 14-20th, the Cook County medical examiner's office recorded 485 heat-related deaths on death certificates (US National Oceanic and Atmospheric Administration 1995). However, when comparing the total number of deaths from all causes with the long-term average of daily deaths for this same time period, Whitman et al. (1997) determined 739 excess deaths attributed to the Chicago heat wave.

Eric Klinenberg, author of *Heat Wave: A Social Autopsy of Disaster in Chicago*, called the 1995 Chicago Heat Wave a social disaster because a significant number of the heat wave deaths resulted from social isolation (University of Chicago 2002). Men were more than twice as likely to die from the heat than women, and the African American/White mortality ratio was 1.5 to 1 (Semenza et al. 1996). Individuals who were confined to a bed, often elderly with medical conditions, as well as those living alone, had the greatest odds of heat-related death. These findings may be explained by the loss of social relationships by elderly men and characteristics (i.e., low income and abandoned) of the African American neighborhoods with high heat wave death rates (University of Chicago 2002).

Along with social isolation, certain spatial factors increase the risk for heat-related illness. Semenza et al. (1996) found those who lived on the top floor of buildings had a greater risk of heat-related death, and those with access to air conditioning and transportation had a reduced risk of heat-related death. Lastly, living in urban areas increases one's risk of heat-related illness over living in rural areas, which can be ascribed to the urban heat island effect – the next section will define this phenomenon, its drivers, and its relation to public health.

2.5.3 Urban Heat Islands

The urban heat island (UHI) effect – the phenomenon in which cities experience higher temperatures than surrounding rural areas – has been measured to increase annual mean air temperatures in cities over rural areas during both the day (1.8-5.4˚F) and night (12.6-21.6˚F) (Figure 6) (Oke 1997, Oke 1987). Occurring independent of the global greenhouse effect, UHIs take place at regional and local scales, and have been found to directly increase the risk of mortality during hot summer days (Tan et al. 2010, Laaidi et al. 2012, Smargiassi et al. 2009). Climate scientists have identified four principle drivers of the UHI: loss of vegetation, high amounts of impervious materials, urban morphology, and waste heat from mechanical processes (Stone Jr 2012a). This section will detail how changes to land surface (i.e., vegetation, impervious materials, and urban morphology) and emissions of waste heat energy from development cause city warming.

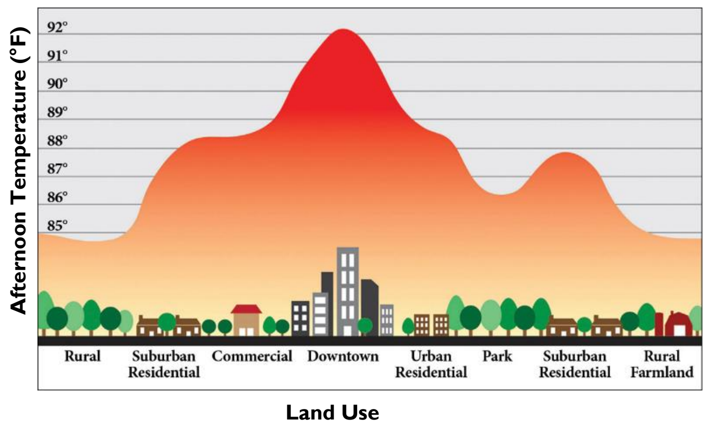

Figure 6. The urban heat island effect.

Source: Bay Area Monitor (2017)

Across the US from 2009-2014, development of urban and community land, as defined by the US Census Bureau, has led to a decrease in tree cover of 175,000 acres per year, or 36 million trees per year (Nowak and Greenfield 2018). Loss of urban vegetation is a major public health concern because vegetation plays a significant role in reducing urban temperatures, cooling the surrounding environment through two main mechanisms: evapotranspiration and shading.

Evapotranspiration, a combined term for evaporation and transpiration, is the "physical mechanism through which heat energy is used by soils and plants to convert water to water vapor" (Stone Jr 2006). Transpiration in plants has a dual purpose of cooling the plants and allowing for the collection of an input for photosynthesis, carbon dioxide.

In evapotranspiration, both water from the ground surface and plants utilize energy, called latent heat, for the required work to change phase from water to water vapor. Latent heat does not result in a temperature change in the air until the water vapor has risen farther up the troposphere, cools, and condenses back into water (Oke 1987).

Another factor of vegetation that cools the microclimate is shade. Tree canopy (i.e., the branches and leaves above a tree's trunk), supplies shade to the surrounding land surface, casting shadows in different spots based on the Sun's diurnal movement. Shashua-Bar and Hoffman (2000) found that in Tel-Aviv during the summer, urban sites with trees were on average 2.8˚C cooler at noon than urban sites without trees, with tree shading contributing 80% of total cooling. Another study found physiological equivalent temperature – the air temperature at which, in a typical indoor setting, the heat budget of the human body is balanced with the same core and skin temperature as assessed outdoor conditions – was 14˚C cooler in shaded over unshaded locations during the summer (Höppe 1999).

Several features common to urban areas (e.g., buildings, streets, and parking lots) are composed of impervious materials, such as concrete and asphalt, that do not allow the infiltration of rainwater and other liquids. Climatologists have learned through thermal remote sensing that a positive relationship exists between impervious surfaces and surface heat islands (Imhoff et al. 2010, Yuan and Bauer 2007). Impervious surfaces have increased from 25.6 to 26.6% in urban areas across the US from 2009-2014, which equates to an annual increase of 131,000 acres of impervious cover per year (Nowak and Greenfield 2018). Impervious surfaces warm the surrounding environment through three main properties: low albedo, high thermal emittance, and reduced evapotranspiration.

Impervious surfaces have relatively low albedo, or reflectivity, meaning a high percentage of the incident solar radiation is not reflected away from the surface, but absorbed by the material. The Earth as a whole has an average albedo of 0.30 (US Environmental Protection Agency 2016a), while manmade materials such as asphalt and concrete exhibit albedos in the ranges of 0.04 - 0.16 and 0.18 - 0.35 (Pomerantz et al. 2003). These materials absorb and store a high proportion of incident solar radiation, leading to surface heat islands. Taha et al. (2018) found that albedo enhancement can reduce neighborhood-scale (500m) air temperatures by as much as 2.8˚C during the daytime.

Impervious materials also have relatively high thermal emittance, defined as the "ratio of energy radiated by the surface to the energy radiated by a black body (a perfect absorber and emitter) at the same temperature" (US Department of Transportation 2015). Concrete and asphalt having emittance values ranging from 0.90 - 0.95 (US Department of Transportation 2015). During the day, these absorptive materials store the energy, releasing sensible heat (i.e., heat that one can feel) during the late afternoon and night. Oke (1987) reasons urban surfaces store more energy due to the "insulation provided by rural vegetation covers, the greater surface area for absorption imparted by urban geometry, or the reduced latent heat uptake due to the relative dryness of urban materials."

Impervious surfaces do not offer the convective cooling ability of the natural surfaces (e.g., vegetation, soil, and open water) that were originally in its place. Urban areas, with extensive impervious surfaces, have generally more stormwater runoff than their rural counterparts. The runoff water drains quickly and, in time, less surface water remains available for evapotranspiration, thus affecting the urban surface energy balance by increasing the amount of sensible heat and decreasing the amount of latent heat (Taha 1997, Yuan and Bauer 2007).

While buildings, streets, and parking lots are constructed of impervious surfaces that generally exhibit lower albedo (higher absorptivity), greater heat storage, and greater emittance than natural surfaces, urban morphology plays a role in how energy, both short-wave and long-wave, travels within space. Cities have what is called an urban canyon, which consists of building walls and the street/ground between the buildings. Due to the sun rising in the east and setting in the west, the energy balance of urban canyons is oriented in a north-south direction. Ali-Toudert and Mayer (2006) found east-west streets tended to be warmer than north-south streets because of a longer exposure to solar radiation. During the day, urban canyons are cooler as the radiative heat surplus is convected out of the canyon, but at night, radiative losses are supplied by conduction from heat storage from impervious canyon materials. Buildings decrease the solar radiation receipt in areas that are shadowed, increase the solar radiation receipt via reflection off sunlit walls, and reduce cooling of areas near buildings due to a reduced sky view factor – the amount of sky visible when viewed from the ground up (Oke 1987).

One quantitative measure for urban street canyons is the aspect ratio, which is the ratio of building height over the distance between buildings (i.e., height divided by width). A higher aspect ratio means a reduced sky view factor, which decreases net outgoing heat. Johansson (2006) found daytime air temperatures to be 10˚C lower in deep canyons over shallow canyons, but that this trend reversed at night, as the nighttime urban heat island intensity was greater in the deep canyon than the shallow canyon.

Lastly, waste heat differs from the other principle UHI drivers (i.e., loss of vegetation, high amounts of impervious materials, and urban morphology) in that it is not based on changes to the land surface. Instead, waste heat originates from mechanical processes, such as motor vehicle travel and space heating and cooling, that are more prevalent in cities than rural areas. This anthropogenic heat is ancient heat, created beneath the surface by years of pressure and temperature.

Waste energy consumption has been estimated to account for about one-third of the UHI effect in Portland, Oregon (Hart and Sailor 2009). Currently, the internal combustion engines in most automobiles are 65% efficient (American Society of Mechanical Engineers 2012); the remaining 35% of energy entering the system as fossil fuels leaves the system as waste heat, warming the surrounding air. Waste heat from cars account for 50-60% of the total waste heat during the summer (Stone Jr 2012b). Furthermore, Salamanca et al. (2014) estimated that heat emitted from air conditioning systems increased the mean air temperature by more than 1°C at night in Phoenix, Arizona.

2.6 Contributions of this Work

To date, the physical activity literature recognizes the use of Ecological Models as a framework to test what factors correlate with physical activity, and research has covered a host of correlates of physical activity across multiple levels of influence (Bauman et al. 2012, Bingham et al. 2016, Sallis, Prochaska, and Taylor 2000). Yet while health behavior models have focused on individual-level correlates of physical activity, the literature examining the relationship between physical activity and environmental factors is underdeveloped.

This work aims to add to the literature around physical activity and the environment, specifically the link between temperature and physical activity; Figure 7 shows the specific contributions of this work in the context of the Ecological Model of four domains of active living. All factors of interest except for the ‘safety’ variable fall within the Behavior Settings level of the Ecological Model and can be further categorized into characteristics of the built environment, access to behavior settings, and the cross-cutting Natural Environment level. This work partitions physical activity based on active living domain into outdoor (i.e., active recreation, active transport, and occupational activities), indoor (i.e., active recreation, household activities, and occupational activities), and total (i.e., active recreation, active transport, household activities, and occupational activities) physical activity.

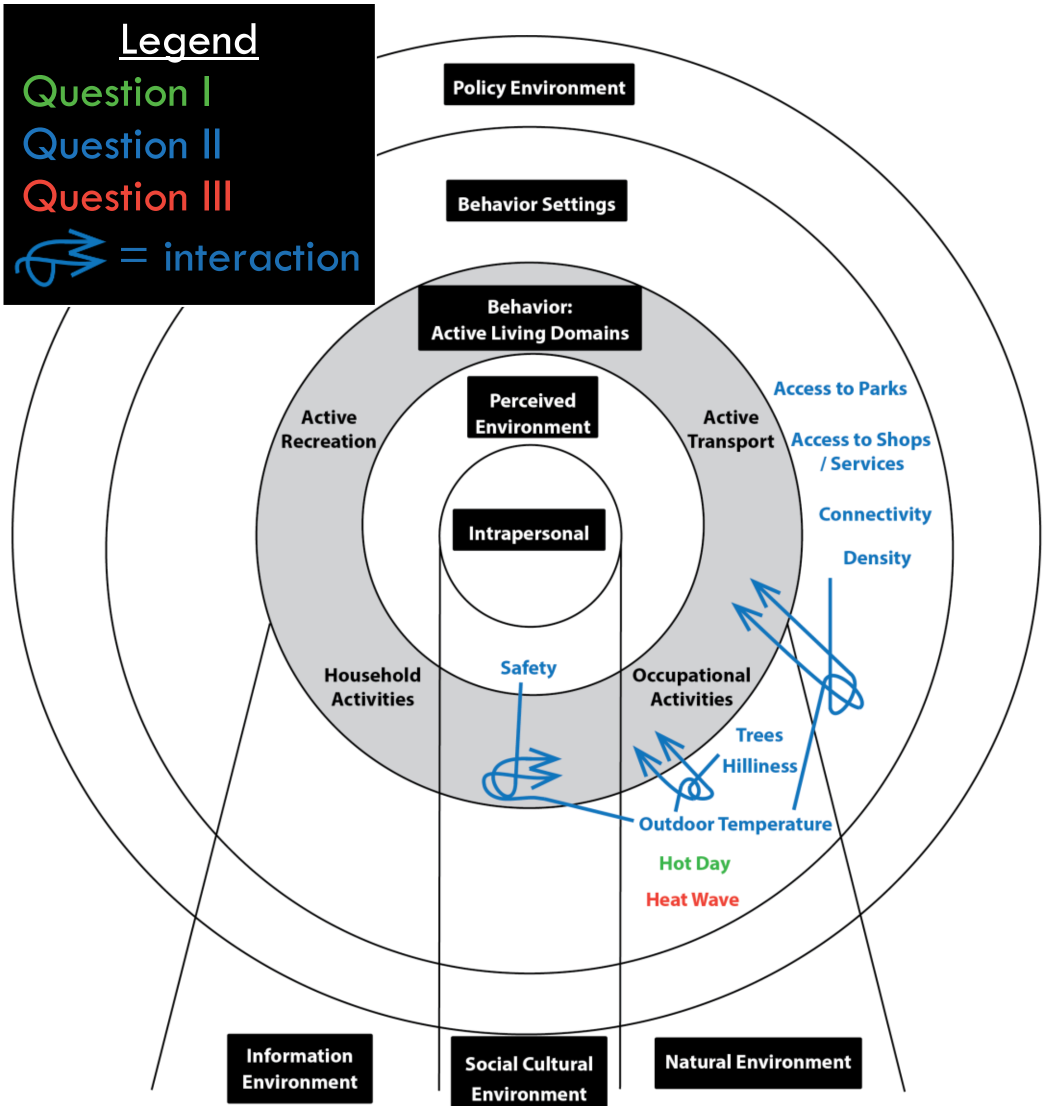

Figure 7. Contributions of this work to research and practice within an Ecological Model.

Chapter 4 covers Question I: How do hot days (found within the Natural Environment level of the Ecological Model) associate with outdoor, indoor, and total physical activity behavior across all active living domains? This chapter serves as a baseline for the other two study questions by concentrating on hot days, as defined by maximum daily heat index, while controlling for other factors that have been shown to correlate with physical activity. Past research has investigated the link between temperature and physical activity levels, but none focus on defined hot days, and only a handful of studies take place in hot, humid environments. Furthermore, research does not examine whether extreme heat has different impacts on outdoor, indoor, and total physical activity. The findings from this chapter can help resolve the inconsistent findings of heat on physical activity levels, as well as provide public health professionals with evidence as to whether individuals are choosing to be physically active during those days with the greatest chance of heat-related illness.

Chapter 5 covers Question II: How do hot days influence the observed effect of built environment factors (found within the Behavior Settings, Natural Environment, Perceived Environment, and Social Cultural Environment levels of the Ecological Model) on outdoor physical activity behavior across all active living domains? This chapter builds on Chapter 4 by assessing the impact of seven different built environment factors, along with hot days, on outdoor physical activity. Past research has evaluated the associations between temperature and/or built environment factors with physical activity, but a search of the literature found no studies have assessed how hot days, as defined by maximum daily heat index, and built environment factors interact to impact outdoor physical activity. The findings from this chapter can assist local government officials and city planners on how to design urban environments to increase physical activity of residents in the face of current and projected urban warming.

Lastly, Chapter 6 covers Question III: How does the weather condition of heat waves (found within the Natural Environment level of the Ecological Model) associate with outdoor, indoor, and total physical activity behavior across all active living domains? This chapter builds on Chapter 4 by examining how a string of consecutive hot days, as defined by maximum daily heat index, impacts physical activity, a research question that has not been covered in the physical activity literature. The findings from this chapter can help public health professionals understand whether heat waves – the likes of which are projected to increase with climate change – impact physical activity levels, specifically whether the length of the heat wave impacts physical activity and whether the effect of a heat wave has a varied effect depending on physical activity location (i.e., outdoor, indoor, and total).

2.7 Conclusion

This chapter presented the state of the literature around how the environment (i.e., temperature and the built environment) influences health (i.e., physical activity and heat-related illness). With this information in hand, the purpose of this study is to narrow the knowledge gap concerning the effect of heat on physical activity levels, that is, the effect of elevated heat found in cities during the summer. A better understanding of the heat-physical activity relationship can inform weather reporting, physical activity interventions, and health impact assessments in the face of urbanization and climate change. Moreover, the discovery of associations between extreme heat and physical activity in cities can facilitate the development of comprehensive and effective urban heat management studies through the lens of physical activity, replete with adaptation strategies to increase thermal comfort and consequently improve public health at the population level.

CHAPTER 3. DESCRIPTION OF THE STUDY

3.1 Introduction

With the relevant literature to this study reviewed and knowledge gaps of interest identified, this chapter begins the formal account of the work and serves as a guide for the remaining chapters. With this work obtaining most of its data, and several components of its design, from a National Science Foundation project awarded in 2015, this chapter provides an explanation of content that is congruent amongst the three central research questions, each of which are to be covered in detail in Chapters 4-6.

The next section of this chapter outlines the three central research questions in this work, followed by sections that cover the specific commonalities among the questions. In particular, this chapter discusses the study sample and selection of study days, the definitions of the focal study measures (i.e., physical activity and heat) and control variables that share the same design across the central research questions, and the type of statistical modeling implemented for all questions. Each research design decision of this work, such as the selected definitions for hot days and heat waves, was based off theory from past literature, and when no precedence existed, decisions were based off logic to produce the most valid, unbiased outcome to each central research question.

3.2 Central Research Questions

3.2.1 Hot Days and Physical Activity

Illustrated below (Figure 8) and to be covered in detail in Chapter 4, the first question of this work is:

How do hot days associate with outdoor, indoor, and total physical activity behavior across all active living domains?

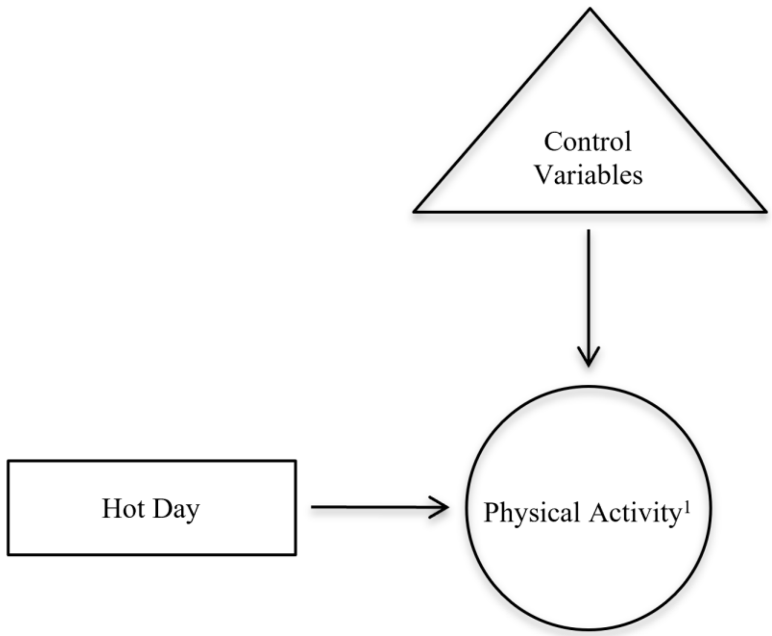

Figure 8. The association between hot days and physical activity (Question 1).
[1]Separate models for outdoor, indoor, and total physical activity.

3.2.2 Hot Days, Built Environment, and Physical Activity

Illustrated below (Figure 9) and to be covered in detail in Chapter 5, the second question of this work is:

How do hot days influence the effect of built environment factors on outdoor physical activity behavior across all active living domains?

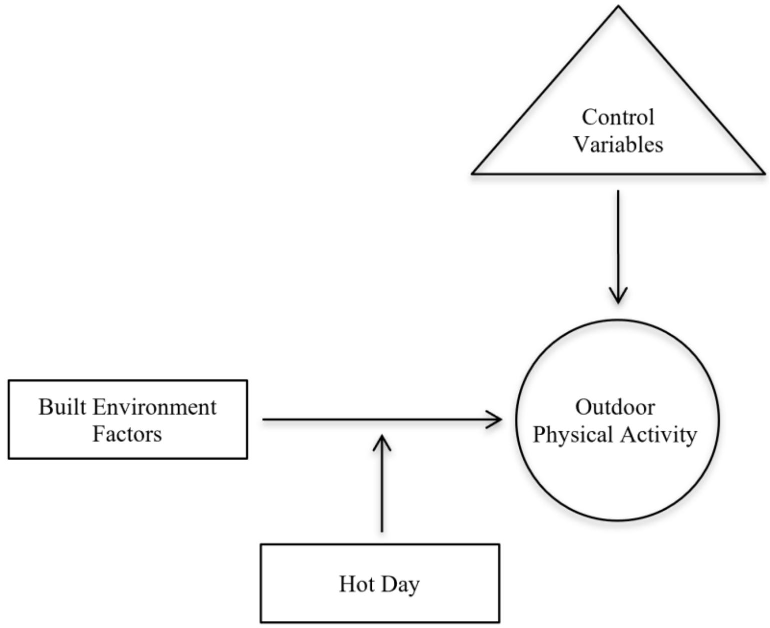

Figure 9. The influence of a hot day on the effect of built environment factors on outdoor physical activity (Question 2).

3.2.3 Heat Waves and Physical Activity

Illustrated below (Figure 10) and to be covered in detail in Chapter 6, the third question of this work is:

How do heat waves associate with outdoor, indoor, and total physical activity behavior across all active living domains?

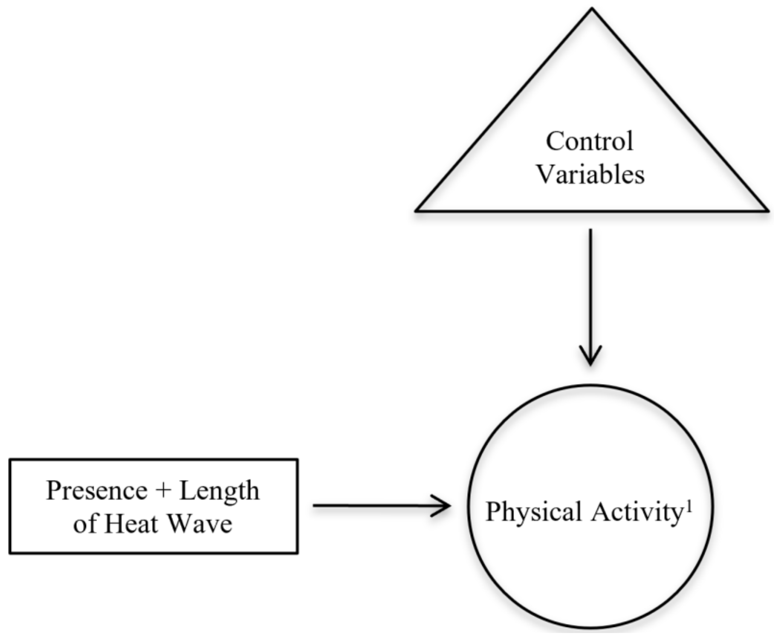

Figure 10. The association between the presence + length of a heat wave and physical activity (Question 3).
[1]***Separate models for outdoor, indoor, and total physical activity.***

3.3 Study Sample

To answer the three central research questions surrounding how summer heat affects physical activity levels, this work relies primarily on data from the National Science Foundation project titled "Hazards SEES: Enhancing Emergency Preparedness for Critical Infrastructure Failure during Extreme Heat Events" (NSF award number: 1520803), also known as the Three City Study of Heat and Electrical Failure Adaptation (3HEAT), the acronym which will be used for the rest of this work. 3HEAT is led by principal investigator Dr. Brian Stone and the co-principal investigators of Drs. Matei Georgescu and Marie O'Neill, who direct research teams at Georgia Institute of Technology, Arizona State University, and University of Michigan, respectively. The core foci of 3HEAT are twofold: 1) to estimate the human health risk of power outages during periods of extreme heat in Atlanta, Detroit, and Phoenix; and 2) to estimate how behavioral, environmental, and technological changes mitigate the health impact of extreme heat. 3HEAT, and consequently this work, takes place in the US cities of Atlanta, GA, Detroit, MI, and Phoenix, AZ (Figure 11), selected due to their distinct climatic, demographic, and urban form characteristics, as well as the association between each city with one of the three university teams.

Atlanta, GA　　Detroit, MI　　Phoenix, AZ

Figure 11. Study sites: Atlanta (134 mi^2), Detroit (142.9 mi^2), and Phoenix (517 mi^2). Source: US Department of Agriculture (n.d.)

This study's sample of adults from Atlanta, Detroit, and Phoenix comes from Phase II of 3HEAT in which research teams collected household- and individual-level data including temperature exposure and physical activity. The teams reached this study population by oversampling individuals who lacked consistent access to air-conditioned settings in an initial screening survey (Phase I) and then asking participants whether they would like to participate in Phase II. From Phase II, the research teams learned how individually experienced temperatures – temperatures immediately surrounding an individual while completing daily activities – vary with time-of-day, location, activity, cooling method, and thermal comfort. The Phase II study population consists of a spatial mix of adults that aims to approximate the demographic composition for each city based on 2010 US Census data (Table 1).

Table 1. Select descriptive statistics for study population of 3HEAT Phase II compared to 2010 US Census data in Atlanta (ATL), Detroit (DET), and Phoenix (PHX).

Source: US Census Bureau (2010b)

	ATL Sample	ATL Census 2010	DET Sample	DET Census 2010	PHX Sample	PHX Census 2010
Sample size	(n = 57)[1]	420,003	(n = 53)	703,000	(n = 46)	1,445,632
Female	56%	50%	89%	53%	59%	50%
White	52%	39%	11%	11%	59%	66%
Median age (years)	43	33	45	35	48	32
Median household income	$40,001 - 60,000	$47,527	$20,000 and under	$25,764	$60,001 - 80,000	$47,326

[1]*lack responses from three participants.*

To capture this study population, the 3HEAT research teams employed a variety of non-random sampling techniques. For Atlanta, the Georgia Tech team recruited within the Georgia Tech network by word-of-mouth and study flyers as well as the Garden Hills section of the Buckhead neighborhood by the Nextdoor website. Georgia Tech also partnered with the EPA Region 4's Office of Environmental Justice and Sustainability to identify study participants in English Avenue and Vine City, two historically African American and low-income neighborhoods.

For Detroit, the University of Michigan team randomly selected study participants within several housing type categories from lists of individuals who had provided or received services from neighborhood organizations partnered with the university: Jefferson East, Inc., Friends of Parkside, and Southwest Detroit Environmental Vision. Community events within Detroit served as another avenue of recruitment.

For Phoenix, the Arizona State University team identified four study sites in the city for recruitment, each of which span approximately five square miles and were chosen for their variety of building types, socioeconomic circumstances, and demographic characteristics within relatively small geographic areas. Within each study site, the team then selected seven neighborhoods that represented the most common combinations of building types and income levels present in that portion of the city and then randomly sampled houses within each.

3.4 Selection of Study Days

From July through September of summer 2016, the 3HEAT research teams asked those enrolled in Phase II of 3HEAT to complete at least six study days, with the number and selection of calendar days differing per study participant and city (Figure 12).

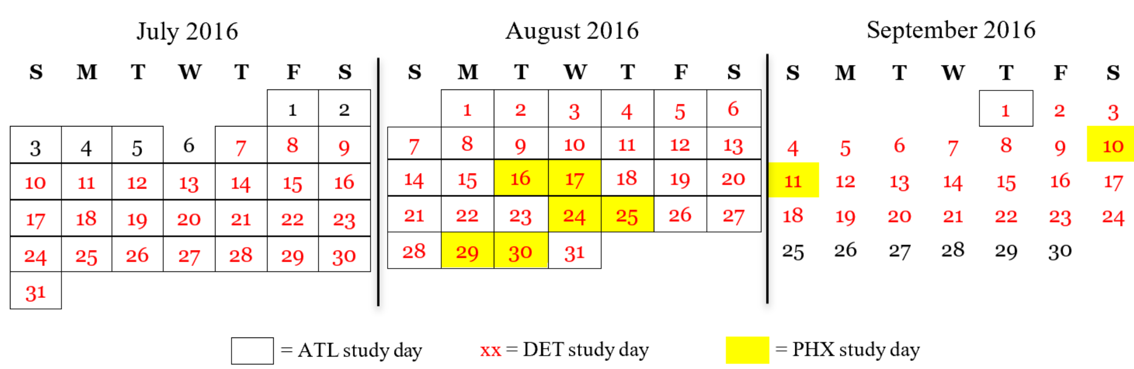

Figure 12. Study days of participants in Atlanta, Detroit, and Phoenix.

The Georgia Tech team informed participants of eligible study days based on forecasted temperatures ≥ 90th percentile of heat from the commercial weather service Weather Underground, yet some participants chose their own study days during the two months, resulting in representation of all days in July and August (except July 6th) as well as the first day in September. The University of Michigan team asked participants to complete at least nine study days: five days forecasted ≥ 88°F and four days forecasted < 88°F. As a result of these guidelines, the Detroit sample covered all days from July 7th through September 24th as study days. The Arizona State team defined eligible study days as those days forecasted to have comparably higher maximum temperatures, which resulted in four two-day periods in July, August, and September. All research teams notified study participants at least 24 hours in advance of eligible study days.

3.5 Measures of Physical Activity

Physical activity data originated from time activity diaries (TADs) filled out by study participants for each study day in Phase II of 3HEAT (Table 2). TADs are 24-hour, continuous, self-reported, written records that, among other items that have no direct relation with this work, detail the length of time spent at a location and the physical activity intensity level(s) at that location (Table 2). Each TAD form provides participants with a choice of four physical activity intensity levels: 1 = sitting or lying down, 2 = light exertion (breathing easy), 3 = moderate exertion (breathing harder), and 4 = heavy exertion (can't have a conversation). APPENDIX A. Time activity diary legend displays the legend for all TAD items.

Table 2. Example portion of a time activity diary (TAD).

Time of Day	Location	Activity Level
5:00-6:26am	Home	1 2 3 4
6:26-6:42am	Sidewalk	1 2 3 4
6:42-7:22am	Home	1 2 3 4
7:22-7:45am	Bike	1 2 3 4
7:45-10:04am	Library	1 2 3 4

After Phase II of 3HEAT concluded in September 2016, the three research teams entered the paper TAD forms into an electronic Google Form and then scored TADs as low, medium, or high quality based on agreed on quality metrics, including whether the inputs for each TAD field were reasonable (e.g., a recorded mode of transportation between two locations) and the temporal resolution of data entry (e.g., minute-to-minute versus hourly reporting). To test the accuracy of data entry, the three teams randomly selected 50% of the low quality, 25% of the medium quality, and 10% of the high-quality TADs to be entered a second time by a different data analyst than the first round of data entry. For these select double-entered TADs, any discrepancies found between the first and second rounds of data entry were identified and resolved.

This work consists of six dependent variables (Figure 13), all of which adopt the same base definition for physical activity: daily percentage of physical activity intensity level during waking hours. This work examined two versions of the dependent variables: "Any Activity" defines physical activity as intensity levels 2-4, while "Recommended Activity" only counts levels 3-4 as physical activity. Both versions of the dependent variable were developed for this study because each test separate constructs. Any Activity assesses whether individuals are exhibiting sedentary behavior, i.e., activities that do not increase energy expenditure significantly above the resting level (Pate, O'Neill, and Lobelo 2008), while Recommended Activity tests whether individuals are participating in moderate-to-vigorous physical activity, i.e., the intensity levels recommended for aerobic physical activity by the national physical activity guidelines. This work incorporates Any Activity along with Recommended Activity because research shows sedentary behavior exhibits independent and qualitatively different effects on metabolism, physical function, and health outcomes than failing to participate in moderate-to-vigorous physical activity (Tremblay et al. 2010). To arrive at the six dependent variables, each version of the dependent variable was stratified by the location of physical activity: outdoors, indoors, and total (i.e., outdoor + indoor).

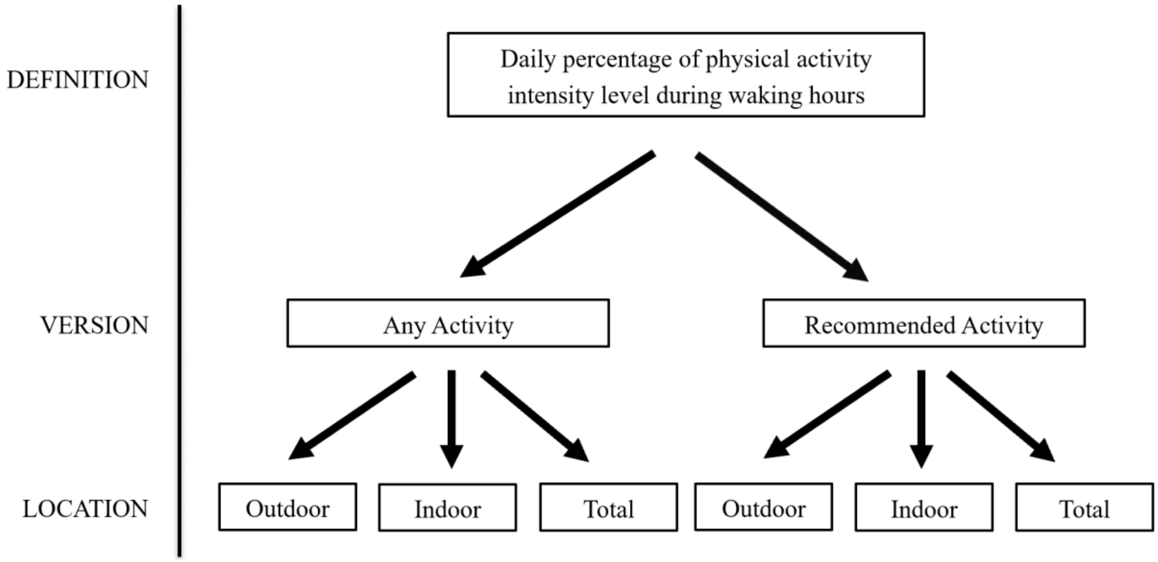

Figure 13. Dependent variables of physical activity (n = 6).

Several data processing decisions were made to arrive at the final six dependent variables. TADs were transformed from 24-hour records to data every 10-minutes in order to match with the temporal resolution of other data collected on Phase II study days: individually experienced temperature and humidity. While completing TADs, study participants wore electronic devices called iButtons (DS1923-F5# Hygrochron Temperature and Humidity iButton) that collected air temperature and relative humidity every five minutes in Atlanta and Phoenix and every 10 minutes in Detroit. Participants wore iButtons outside their clothes on a lanyard around their neck or attached to a carabiner at all times except while sleeping or participating in water activities, such as showering.

This study, not 3HEAT, calculated heat index from airport weather stations (Section 3.6) rather than individual iButtons because local weather forecasts are based on the former, and serve as a more accessible, day-level measure of heat. This work transformed TAD data from continuous measurements to 10-minute intervals for future time-series analyses, not to be covered in this work, that will examine how within-day changes in heat index (calculated from iButton data) associate with physical activity levels throughout the day.

Another motivation for transforming TAD data from continuous to 10-minute intervals was to aid the computation of daily percentage of physical activity. This study only examined physical activity during waking hours, defined as 5am to 10pm, removing nighttime periods because of the traditional lack of physical activity during these hours. These waking hours consist of 102 10-minute intervals, which were then used to detect completeness of the TAD data. The self-reported nature of TADs resulted in instances of missing data throughout the day, with 295 of the 1,122 study days across all study participants including the full suite of 102 10-minute intervals. A review of the data found this relatively low level of completeness was mostly because individuals only started recording TADs once they woke up, which may be considerably after 5am, and stopped recording TADs once they went to bed. This work made the rule that 70% of the 102 10-minute intervals had to be accounted for to be included in subsequent analyses; this rule led to the inclusion of 818 study days, or 72.9% of all study days.

Prior to calculating the six dependent variables for each of the 818 study days, data recorded at locations not conventionally considered indoor or outdoor were removed (APPENDIX B. Location classification for time activity diaries). After creating the dependent variables, study days for those individuals who participated in zero total physical activity (i.e., no outdoor and indoor physical activity) across all study days were removed – a process separately undertaken for each of the two versions of the dependent variable. The rationale behind removing these physically inactive individuals from the study was to limit zero-inflation of the data, a common issue in studies measuring physical activity levels that, if not controlled for, would result in failure of a major assumption of models with a continuous outcome: a normal distribution of the data. Three of the six dependent variables (i.e., daily percentage of outdoor physical activity – Any Activity, daily percentage of outdoor physical activity – Recommended Activity, and daily percentage of indoor physical activity – Recommended Activity) were normalized by log transformation because the distribution of values for these dependent variables remained non-normal after removing study days of physically inactive individuals.

Lastly, the three research teams of 3HEAT advised study participants to record all physical activity intensity levels reached during the time range at a given location, meaning a number of single 10-minute intervals had multiple physical activity intensity levels. This work implemented the decision rule to select the highest-recorded intensity level of physical activity for any given 10-minute interval, as this activity level signifies the peak potential intensity at that time and location.

3.6 Measures of Heat

The climate literature has no standard definition for either hot days or heat waves. Instead, definitions are formulated based on context and purpose, considering characteristics such as the climate of the sites of interest and the health outcome. Current heat wave definitions are pieced together from each of the following: 1) air temperature, heat index, or apparent temperature; 2) temperature metrics of mean, minimum, and/or maximum daily temperature; 3) absolute temperature thresholds or relative thresholds from temperature percentiles, e.g., > 85th, > 90th, > 95th, > 97.5th, > 98th, or 99th; and 4) duration of at least two or three days (Anderson and Bell 2011, Peng et al. 2011, Meehl and Tebaldi 2004, Steadman 1984, Smith, Zaitchik, and Gohlke 2013).

Ultimately, this work defined a "hot day" as a day where heat index was ≥ the 90th percentile of daily maximum heat index during the warm season (May through September) from 2000-2016, and a heat wave as simply two or more consecutive “hot days.” This work chose heat index instead of air temperature to define hot days because a heat index – a combination term of air temperature and relative humidity – better captures thermal sensation or comfort, and air temperature and relative humidity in conjunction impact human thermoregulation. This study chose to define hot days as maximum heat index instead of minimum or average heat index because physical activity takes place during waking hours, the time range when maximum heat index takes place.

This study utilized a relative temperature threshold in lieu of an absolute threshold to ensure hot days were defined by excessively high temperatures that were location-specific for each of the three study cities. An absolute temperature threshold does not suffice for studies examining cities at different latitudes, as a 95˚F day in the Northeast US exhibits a more pronounced effect on health than a 95˚F day in the Southwest US due to differences in heat acclimatization among the two populations. The decision to calculate the 90th percentile of daily maximum heat index from only the warm season instead of the full year ensured hot days were abnormally hot relative to other summer days. The years 2000-2016 were used to capture the most recent climate patterns for each study city.

This work made use of hourly air temperature and relative humidity data from the weather station at each city’s major airport (i.e., Hartsfield-Jackson Atlanta International Airport, Detroit Metropolitan Wayne County Airport, and Phoenix Sky Harbor International Airport) (Table 3). Climate research commonly utilizes data from weather stations at major airports to measure weather conditions of a city because airports tend to maintain weather stations, allowing for a time series that is homogenous – variations are caused only by variations in weather and climate, and not by changes in the 1) location of the station, 2) observing instruments, and 3) time of observation (Stone 2007).

Table 3. Airport weather station characteristics for each study city.

	Atlanta	Detroit	Phoenix
USAF-WBAN ID[1]	722190-13874	725370-94847	722780-23183
Latitude, Longitude	33.630, -84.442	42.231, -83.331	33.428, -112.004
Elevation (meters)	307.9	192.3	337.4

[1]Weather station ID code: US Air Force (USAF)-Weather Bureau Army Navy (WBAN).

To define hot days and heat waves, global hourly surface data were downloaded online from the Integrated Surface Database maintained by the National Climatic Data Center (US National Oceanic and Atmospheric Administration 2018a). First, relative humidity was calculated for each hourly measurement of air temperature and dewpoint from May through September 2000-2016, using Equation 1 provided by the US National Oceanic and Atmospheric Administration (Stephens, Scott. 2018. E-mail message to author, June 26):

$$RH \cong \left[\frac{(173 - 0.1T + Td)}{(173 + 0.9T)}\right]^8 \qquad \text{(Equation 1)}$$

RH = Relative Humidity

T = Temperature (˚F)

Td = Dewpoint (˚F)

Next, heat index was calculated for each hourly measurement of air temperature and the newly calculated relative humidity from May through September 2000-2016. Not one single equation calculates heat index for the full range of air temperature and relative humidity values, so a stepwise approach must be applied. The process begins with Equation 2 from Steadman (1984):

$$HI = 0.5 * \{T + 61.0 + [(T - 68.0) * 1.2] + (RH * 0.094)\} \qquad \text{(Equation 2)}$$

HI = Heat Index (˚F)

T = Temperature (˚F)

RH = Relative Humidity (%)

This computed value is then averaged with the input temperature value, and if this averaged value is < 80˚F, then that is the final heat index value. If the averaged value is ≥ 80˚F, Equation 3 from Rothfusz (1990) must then be applied to the air temperature and relative humidity data:

$$\begin{aligned} HI = {} & -42.379 + 2.04901523 * T + 10.14333127 * RH \\ & - 0.22475541 * T * RH - 0.00683783 * T^2 \\ & - 0.05481717 * RH^2 + 0.00122874 * T^2 * RH \qquad \text{(Equation 3)} \\ & + 0.00085282 * T * RH^2 - 0.00000199 * T^2 \\ & * RH^2 \end{aligned}$$

HI = Heat Index (˚F)

T = Temperature (˚F)

RH = Relative Humidity (%)

The resulting heat index values are final unless air temperature and relative humidity values fall within a select range, at which point adjustments must be applied to the heat index values. If the air temperature value is between 80-112˚F and the relative humidity value is < 13%, then the adjustment in Equation 4 is subtracted from the heat index to obtain the final heat index value (US National Oceanic and Atmospheric Administration 2014):

$$Adjustment = \left[\frac{(13 - RH)}{4}\right] * \sqrt{\left\{\frac{[17 - |(T - 95)|]}{17}\right\}} \qquad \text{(Equation 4)}$$

RH = Relative Humidity (%)

T = Temperature (˚F)

Alternatively, if the air temperature value is between 80-87˚F and the relative humidity value is > 85%, then the adjustment in Equation 5 is added to the heat index to obtain the final heat index value (US National Oceanic and Atmospheric Administration 2014):

$$Adjustment = \left[\frac{(RH - 85)}{10}\right] * \left[\frac{(87 - T)}{5}\right] \qquad \text{(Equation 5)}$$

RH = Relative Humidity (%)

T = Temperature (˚F)

Now with hourly heat index values for all days from May through September 2000-2016, the maximum heat index value was identified for each day. From these values, the

90th percentile of daily maximum heat index was calculated, with the 90th percentile threshold equaling 96.7˚F, 91.5˚F, and 109.3˚F, in Atlanta, Detroit, and Phoenix, respectively. Hot days were identified as those where maximum heat index was at or above the threshold value of the associated city, and heat waves were identified as two or more consecutive days at or above the threshold value.

3.7 Included Control Variables

3.7.1 Individual

In order to concentrate on the specific impact of heat on physical activity, this study accounted for other factors that have been shown to significantly associate with physical activity, with several directly linked to the study participants: sex, race, age, health status, income level, and city of residence.

The literature finds that physical activity levels are higher in adult males and Whites than in females and Non-Whites, respectively, and that as one ages, physical activity levels decrease (US National Center for Health Statistics 2018). Healthy adults are more likely to be physically active than those in poor health (Bauman et al. 2002, Washburn et al. 1993), and higher income levels associate with higher physical activity levels (US National Center for Health Statistics 2018). This study controls for potential differences in physical activity based on city of residence, because each city has its own set of characteristics that either attract or deter physical activity (e.g., culture, physical activity facilities, public parkland, and urban design).

3.7.2 Weather

While heat is the primary weather element of interest, this work controlled for rain because of its role as a barrier to physical activity (Alahmari et al. 2015, Liu, Susilo, and Karlström 2015, Motoaki and Daziano 2015). Precipitation data originate from the same source as the air temperature and relative humidity data (Section 3.7.1): Global hourly surface data collected by weather stations at each city's major airport (Table 3) were downloaded online from the Integrated Surface Database maintained by the National Climatic Data Center (US National Oceanic and Atmospheric Administration 2018a). To identify rainy days, hourly precipitation data – collected as the precipitation in inches for the preceding one-hour period – were examined for all study days during the 2016 Warm Season.

3.7.3 Time

Lastly, this work controlled for weekend days, because the literature shows that the weekend, a period that falls outside of traditional work hours, has a significant association with physical activity levels: The literature finds children to exhibit significantly higher levels of physical activity on weekends (Riddoch et al. 2007, Page et al. 2009, Van Cauwenberghe et al. 2012), while adults – the sample in this work – exhibit mixed associations with physical activity on weekends (O'Donovan et al. 2017, Tudor-Locke et al. 2005).

3.8 Growth Curve Modeling

To test the effect of summer heat on physical activity levels, this work utilized multilevel growth curve models, also called longitudinal multilevel regression models, with linear change over time. While general linear models assume data are uncorrelated and have equal variances, nested data do not follow these assumptions, exhibiting statistical dependency and heteroscedasticity (O'Dwyer and Parker 2014). Multilevel models handle correlated data and unequal variances by considering both fixed effects and random effects that assume a relationship exists between some data. Furthermore, multilevel models allow for the inclusion of cases where there are incomplete data or unequal time spacing between measurement points.

In this study, the repeated observations for a single subject – each study participant reported his or her physical activity levels across multiple days during the summer – means a study participant's study days are more likely to be similar to each other than study days of other study participants. Therefore, this work adopted a two-level growth curve model, with the first level being study day and the second level being study individual. In order to run growth curve models, the data were first transformed from person-level format to person-period format (i.e., wide format where an individual's repeated responses are in a single row and each response is in a separate column to long format where each row is one time point per individual and each individual has data in multiple rows, respectively). In preparation for statistical analyses, data for Atlanta, Detroit, and Phoenix were pooled into one data set to increase statistical power over independent city analyses. The two-level growth curve modeling followed a stepwise approach: 1) unconditional growth model, 2) model adding environmental variables, and 3) a final model adding potential confounders. All statistical analyses were conducted within the statistical package for the social sciences (SPSS, version 24).

3.9 Conclusion

This chapter served to frame the rest of this work by introducing the three central research questions and explaining the components of this work that were shared by each of the central research questions. With this information in hand, this study continues with the formation and testing of hypotheses for each central research question, followed by detailed description of the methodology, model output, and discussion of the results. The final chapter of this work proposes recommendations, based on study findings, to promote safe physical activity in a warming world.

CHAPTER 4. HOT DAYS AND PHYSICAL ACTIVITY

4.1 Introduction

As illustrated in Section 3.2.1, this chapter covers Question 1: How do hot days associate with outdoor, indoor, and total (i.e., outdoor + indoor) physical activity behavior across all active living domains? This central research question can be thought of as a building block for the rest of this work because the other two central research questions adopt the definition of hot day first utilized by Question 1 in some form to develop their focal predictor variables. Secondly, past research has explored the association between temperature and physical activity, whereas no variations of the other two central research questions have been examined. However, Question 1 provides a novel take on the association between heat and physical activity.

The literature (Section **Error! Reference source not found.**) shows the association between temperature and physical activity has been measured at varying temporal scales, which result in different findings: Studies examining the impact of annual seasons on physical activity found physical activity has a positive association with summer months and a negative association with winter months, while studies examining the connection between daily temperature and physical activity exhibit mixed results, with more negative associations at locations near the equator and more positive associations at locations far from the equator. Question 1 adds to the literature by exploring the correlation between daily heat and physical activity at three locations of varying latitudes. Furthermore, this question is original for stratifying physical activity by location (i.e., outdoor, indoor, and total) when investigating the heat – physical activity relationship.

Based on this division into outdoor, indoor, and total physical activity, Question 1 includes three independent research questions with one hypothesis per question. Regarding outdoor physical activity, this study posits that an increase in maximum daily heat index will associate with an increase in outdoor physical activity levels until a certain maximum heat index threshold, at which point there will be a decrease in outdoor physical activity levels. The rationale is that on days where heat index reaches a certain high, individuals will be less active outdoors because of the thermally uncomfortable conditions, which the individual learned of from direct experience and/or accessing weather information.

Regarding indoor physical activity, this study posits that an increase in maximum daily heat index will associate with a decrease in indoor physical activity until a certain maximum heat index threshold, at which point individuals will be more active indoors. The rationale is that individuals prefer outdoor physical activity over indoor physical activity until the heat index becomes too uncomfortable for outdoor activity, at which point individuals will shift their activity from outdoors to indoors in an effort to escape the heat and perform activity in climate-controlled, air-conditioned environments. Regarding total physical activity, this study posits that total physical activity will increase until a certain maximum heat index threshold, at which point there will be a decrease in total physical activity. The rationale is that a larger proportion of an individual's physical activity occurs outdoors versus indoors.

Understanding how hot days associate with outdoor, indoor, and total physical activity levels has practical implications. If summer heat, as hypothesized, significantly decreases outdoor physical activity, increases indoor physical activity, and decreases total physical activity, then public health practitioners should develop methods to further promote physical activity indoors to make up for the reduction in outdoor physical activity. In addition, city planners should implement heat management strategies to reduce temperatures, with the intent of modifying outdoor physical activity behavior.

4.2 Method Details

After the removal of study days missing ≥ 30% TAD data and for those individuals who participated in zero total physical activity across all study days, the study sample included 134 adults and 741 days for dependent variable Any Activity and 117 adults and 717 days for dependent variable Recommended Activity. While Chapter 3 outlines the methods shared by the three central research questions, the remainder of this section describes the methods specific to Question 1. Figure 14 shows that 22, 14, and one study day across Atlanta, Detroit, and Phoenix, respectively, were considered hot days (i.e., ≥ the 90th percentile of daily maximum heat index during the warm season from 2000-2016).

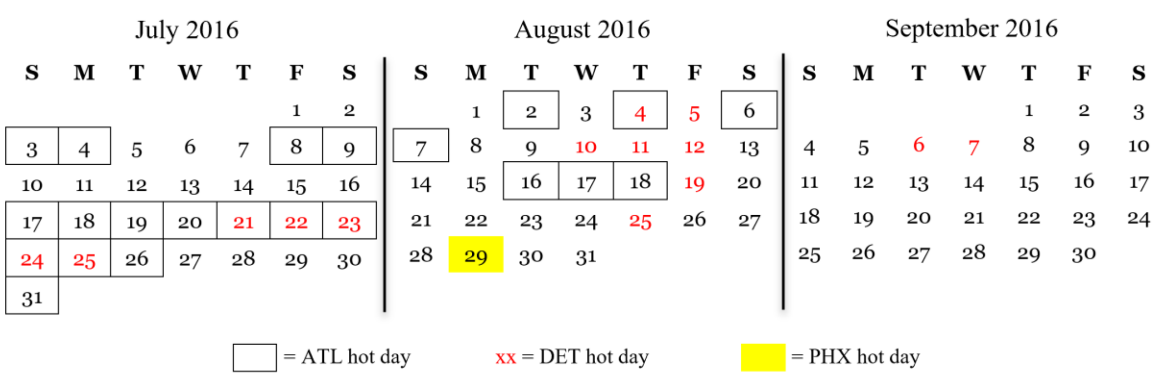

Figure 14. Study days (post data processing) considered hot days in Atlanta, Detroit, and Phoenix.

Descriptive statistics were conducted for all predictor variables on Level 1 of study day and Level 2 of study individual (Table 4), as well as for the six dependent variables of daily percentage of physical activity from the two versions of the dependent variable (i.e., Any Activity and Recommended Activity) and three physical activity locations (i.e., outdoor, indoor, and total). To understand how hot days associate with daily percentage of physical activity, separate two-level growth curve models were run for each of the six dependent variables within SPSS.

Table 4. Predictor variables included in growth curve models (Question 1).

Variable	Metric	Source
	Level 1 Time-Varying Variables	
WEATHER		
Hot day	≥ 90th percentile of max daily heat index (°F)	US National Oceanic and Atmospheric Administration (2018b)
Rainy day	daily precipitation (yes/no)	US National Oceanic and Atmospheric Administration (2018b)
TIME		
Weekend day	weekend (yes/no)	3HEAT (2016)
	Level 2 Time-Invariant Variables	
INDIVIDUAL		
Sex	female (yes/no)	3HEAT (2016)
Race	Non-White (yes/no)	3HEAT (2016)
Age[1]	years	3HEAT (2016)
Health	perceived not good health (yes/no)	3HEAT (2016)
Income	annual household income ($)	3HEAT (2016)
CITY		
Detroit[2]	Detroit (yes/no)	3HEAT (2016)
Phoenix[2]	Phoenix (yes/no)	3HEAT (2016)

[1]Age variable was mean-centered to aid interpretability and protect against multicollinearity.

[2]Omitted category = Atlanta.

To arrive at the full growth curve model, this analysis included a succession of three growth curve models (Models 1-3), where each model built off the previous model: Model 1 was the unconditional growth model with dependent variable, time indicator variable, and intercepts; Model 2 added hot day and rainy day; and Model 3 added weekend day, sex, race, age, health, income, Detroit, and Phoenix. The Level 1, Level 2, and Mixed formulas for the proposed final model are displayed below (Equation 6):

(Level 1) (Equation 6)

$$PhysicalActivity_{ti} = \pi_{0i} + \pi_{1i} * Time_{ti} + \pi_{2i} * HotDay_{ti} + \pi_{3i} * RainyDay_{ti} + \pi_{4i} * WeekendDay_{ti} + e_{ti}$$

(Level 2)

$$\pi_{0i} = \beta_{00} + \beta_{10} * Sex_i + \beta_{20} * Race_i + \beta_{30} * Age_i + \beta_{40} * Health_i + \beta_{50} * Income_i + \beta_{60} * City_i + r_{0i}$$

$$\pi_{1i} = \beta_{10}$$

$$\pi_{2i} = \beta_{20}$$

$$\pi_{3i} = \beta_{30}$$

$$\pi_{3i} = \beta_{40}$$

(Mixed)

$$PhysicalActivity_{ti} = \beta_{00} + \beta_{10} * Sex_i + \beta_{20} * Race_i + \beta_{30} * Age_i + \beta_{40} * Health_i + \beta_{50} * Income_i + \beta_{60} * City_i + \beta_{10} * Time_{ti} + \beta_{20} * HotDay_{ti} + \beta_{30} * RainyDay_{ti} + \beta_{40} * WeekendDay_{ti} + r_{0i} + e_{ti}$$

4.3 Results

Table 5 reports the pooled three-city descriptive statistics for all model variables on Levels 1 and 2. Regarding individual demographics, approximately a quarter of study individuals perceived themselves as not of good health. On average, the study sample was more female (64.9% vs. 50.8%), more Non-White (52.2% vs. 27.6%), older (44.9 vs. 37.2 years), and more affluent ($65,130 vs. $55,322) than the US population as a whole (US Census Bureau 2010b). Regarding physical activity, the average study individual spent about half the day participating in Any Activity and about a tenth of the day participating in Recommended Activity. A larger percentage of physical activity – both Any Activity and Recommended Activity – took place indoors over outdoors, as individuals spent more time indoors throughout the day. The average heat index of all study days was 95.7°F. Hot days, rainy days, and weekend days constituted 43.5%, 27.4%, and 24.0% of study days, respectively.

APPENDIX C. descriptive statistics per City shows the descriptive statistics of the study sample per city. On average, the samples approximated the populations for each city captured by the 2010 Census (Table 1), except that the Atlanta sample was significantly less Non-White (45.5% vs. 61%) and more affluent ($79,787 vs. $47,527), the Detroit sample was significantly more female (90.7% vs. 53%), and the Phoenix sample was significantly older (47.6 vs. 32 years) and more affluent ($88,125 vs. $47,326). For all cities, a larger percentage of physical activity – both Any Activity and Recommended Activity – took place indoors over outdoors. Of the three cities, Detroit had the largest daily percentage of Any Activity (51.9%), Recommended Activity (16.0%), and indoor Recommended Activity (12.2%), while Phoenix had the smallest daily percentage of outdoor Any Activity (4.8%). The percentage of study days defined as hot days varied per city (i.e., Atlanta = 70.4%, Detroit = 28.1%, and Phoenix = 15.9%), with Atlanta as the only city where the average heat index (98.6˚F) of study days was above the minimum heat index threshold used to define hot days (96.7˚F).

Table 5. Pooled three-city descriptive statistics (Question 1).

Variable	Count	% of Total	Mean	Standard Deviation
Level 1 Time-Varying Variables[1]				
PHYSICAL ACTIVITY				
Any activity, outdoor (%)			6.8	11.0

Any activity, indoor (%)			40.8	28.1
Any activity, total (%)			47.5	28.1
Recommended activity, outdoor (%)			3.6	8.7
Recommended activity, indoor (%)			8.0	15.4
Recommended activity, total (%)			11.6	17.5
WEATHER				
Heat index (°F)			95.7	8.5
Hot day	322	43.5		
Rainy day	203	27.4		
TIME				
Weekend day	178	24.0		
***Level 2 Time-Invariant Variables*[2]**				
INDIVIDUAL				
Sex (female)	87	64.9		
Race (Non-White)	70	52.2		
Age (years)			44.9	16.6
Health (not good health)	35	26.1		
Income ($)			65,130	59,388

[1]Based on 741 days from dependent variable Any Activity (i.e., physical activity defined as intensity levels 2-4). Dependent variable Recommended Activity (i.e., physical activity defined as intensity levels 3-4) removes 24 days across the three cities.

[2]Based on 134 individuals from dependent variable Any Activity (i.e., physical activity defined as intensity levels 2-4). Dependent variable Recommended Activity (i.e., physical activity defined as intensity levels 3-4) removes 17 individuals across the three cities.

This work focused on the model output for dependent variable version Any Activity (Tables 6-8) over Recommended Activity (APPENDIX D. Results: How hot days associate with physical activity (Recommended Activity)), because the former had less study days with zero physical activity per physical activity location (i.e., 41% zero outdoor activity, 12% zero indoor activity, and 5% zero total activity) than the latter (i.e., 68% zero outdoor activity, 63% zero indoor activity, and 43% zero total activity), resulting in improved data distribution. However, the model output for both versions Any Activity and Recommended Activity showed equal significance of association between focal predictors and activity.

Within the three-model sets for Any Activity outdoor, indoor, and total, this analysis reported on Model 3 because this final, most elaborate model had the best fit, as determined by proportional reduction in variance, the most established measure to assess the predictive ability of multilevel models (Singer, Willett, and Willett 2003), and Akaike information criterion (AIC) and Bayesian information criterion (BIC), with lower AIC and BIC values from model to model signifying smaller deviance, that is, better model fit.

Within the three-model sets for Any Activity outdoor, indoor, and total, model fit improved from Models 1 to 3, as determined by an increased reduction in τ_{00} and σ^2, along with decreasing values for AIC and BIC.

For outdoor physical activity (Table 6), Model 3 accounted for 5.60% of the variance of the intercept (Level 2), and the statistically significant value for the unexplained variance at baseline indicates that there are other, omitted factors that can explain outdoor physical activity. Model 3 accounted for 36.0% of the within group (Level 1) variance, with the remaining variance not found to be statistically significant. Model 3 estimated that the focal predictor of hot day ($\beta = 0.01$, $p = 0.91$) did not have a significant association with the log of daily percentage of outdoor physical activity, holding all other variables constant.

Among control variables, Model 3 predicted that being female associated with a 43% decrease in the log of daily percentage of outdoor physical activity ($p = 0.03$). The final model also estimated that being Non-White corresponded with a 36% decrease in the log of daily percentage of outdoor physical activity ($p = 0.08$). Lastly, the model predicted that every one-year increase in age above 44.9 years associated with a 1% decrease in the log of daily percentage of outdoor physical activity ($p = 0.08$). All other model variables exhibited insignificant associations with the log of daily percentage of outdoor physical activity ($p > 0.10$).

Table 6. Model results: How hot days associate with outdoor physical activity.

	Model 1	Model 2	Model 3
Fixed effects			
Intercept	1.30***	1.31***	1.88***
Level 1-time-varying variables			

Weather			
Hot Day (0 = not hot day)		0.02	0.01
Rainy Day (0 = not rainy day)		-0.08	-0.13
Weekend Day (0 = not weekend day)			-0.01
Level 2-time-invariant variables			
Individual			
Sex (0 = male)			-0.43**
Race (0 = White)			-0.36*
Age (0 = 44.9 years)[1]			-0.01*
Health (0 = good health)			-0.31
Income ($)			0.01
City of Residence[2]			
Detroit (0 = not Detroit)			0.12
Phoenix (0 = not Phoenix)			-0.23
Random effects			
τ_{00} (intercept)	0.57***	0.57***	0.54***
σ^2	0.04	0.04	0.03
Model fit			
Reduction in τ_{00}		-0.08 %	5.60 %
Reduction in σ^2		-2.42 %	36.0 %
AIC	2,265.6	2,270.8	1,747.8
BIC	2,279.4	2,284.6	1,760.9

Dependent variable: log of daily percentage of outdoor physical activity, Any Activity.
* p < 0.10 ** p < 0.05 *** p < 0.01

[1]Age variable was mean-centered to aid interpretability and protect against multicollinearity.

[2]Omitted category = Atlanta.

For indoor physical activity (Table 7), Model 3 accounted for 1.32% of the variance of the intercept (Level 2), and the statistically significant value for the unexplained variance at baseline indicates that there are other, omitted factors that can explain indoor physical activity. Model 3 accounted for -26.1% of the within group (Level 1) variance, with the remaining variance found to be statistically significant. Model 3 estimated that the focal predictor of hot day ($\beta = 1.32$, $p = 0.52$) did not have a significant association with the daily percentage of indoor physical activity, holding all other variables constant. Model 3 predicted that being female associated with a 9.39% increase in daily indoor physical activity ($p = 0.06$). All other model variables exhibited insignificant associations with daily percentage of indoor physical activity ($p > 0.10$).

Table 7. Model results: How hot days associate with indoor physical activity.

	Model 1	Model 2	Model 3
Fixed effects			
Intercept	42.15***	40.97***	40.15***
Level 1-time-varying variables			
Weather			
Hot Day (0 = not hot day)		1.66	1.32
Rainy Day (0 = not rainy day)		1.83	2.31
Weekend Day (0 = not weekend day)			-2.29
Level 2-time-invariant variables			
Individual			
Sex (0 = male)			9.39*
Race (0 = White)			-6.84
Age (0 = 44.9 years)[1]			-0.12
Health (0 = good health)			3.03
Income ($)			-1.30
City of Residence[2]			
Detroit (0 = not Detroit)			6.41
Phoenix (0 = not Phoenix)			2.67
Random effects			
τ_{00} (intercept)	364.69***	366.44***	361.60***
σ^2	0.10*	0.10*	0.13**
Model fit			
Reduction in τ_{00}		-0.48 %	1.32 %
Reduction in σ^2		-4.00 %	-26.1 %
AIC	6,758.4	6,750.4	5,291.1
BIC	6,772.2	6,764.2	5,304.1

Dependent variable: daily percentage of indoor physical activity, Any Activity.

* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

[1]Age variable was mean-centered to aid interpretability and protect against multicollinearity.

[2]Omitted category = Atlanta.

For total physical activity (Table 8), Model 3 accounted for 3.45% of the variance of the intercept (Level 2), and the statistically significant value for the unexplained variance at baseline indicates that there are other, omitted factors that can explain total physical activity. Model 3 accounted for -27.7% of the within group (Level 1) variance, with the remaining variance found to be statistically significant. Model 3 estimated that the focal predictor of hot day ($\beta = 0.01$, $p = 0.91$) did not have a significant association with the daily percentage of total physical activity, holding all other variables constant. Model 3 predicted that every one-year increase in age above 44.9 years associated with a -0.22 decrease in the daily percentage of total physical activity (p = 0.09). All other model variables exhibited insignificant associations with daily percentage of total physical activity (p > 0.10).

Table 8. Model results: How hot days associate with total physical activity.

	Model 1	Model 2	Model 3
Fixed effects			
Intercept	49.35^{***}	48.66^{***}	48.80^{***}
Level 1-time-varying variables			
Weather			
Hot Day (0 = not hot day)		1.08	1.60
Rainy Day (0 = not rainy day)		0.86	0.87
Weekend Day (0 = not weekend day)			-1.96
Level 2-time-invariant variables			
Individual			
Sex (0 = male)			5.48
Race (0 = White)			-7.07
Age (0 = 44.9 years)[1]			-0.22^{*}
Health (0 = good health)			1.10
Income ($)			-1.18
City of Residence[2]			
Detroit (0 = not Detroit)			9.44
Phoenix (0 = not Phoenix)			3.52
Random effects			
τ_{00} (intercept)	349.41^{***}	349.91^{***}	337.85^{***}
σ^2	0.11^{*}	0.11^{*}	0.14^{**}
Model fit			
Reduction in τ_{00}		-0.14 %	3.45 %
Reduction in σ^2		-2.53 %	-27.7 %
AIC	6,745.6	6,739.0	5,283.3
BIC	6,759.4	6,752.8	5,296.3

Dependent variable: daily percentage of total physical activity, Any Activity.

* p < 0.10 ** p < 0.05 *** p < 0.01

[1]Age variable was mean-centered to aid interpretability and protect against multicollinearity.

[2]Omitted category = Atlanta.

4.4 Discussion

The final growth curve models found that hot days – days ≥ 90th percentile of maximum daily heat index – did not have a significant association with daily percentage of outdoor, indoor, and total physical activity of adults. These results do not corroborate with the stated hypotheses. Relatively hot summer days did not decrease outdoor physical activity levels because of thermally uncomfortable ambient conditions, nor did the heat increase physical activity in indoor, potentially air-conditioned environments. Hot days did not exhibit a significant impact on total physical activity levels, which suggests that heat, at the levels experienced by the sample, does not influence an individual's ability to participate in health-protective levels of physical activity. In light of this, cities need not take hot days into account when developing strategies to promote physical activity of its residents.

Based on model results (Tables 6-8), individuals may have a higher behavioral threshold for heat than the prescribed definition for hot days because of heat acclimatization – the beneficial physiological adaptations from repeated exposure to hot environmental conditions that allow the body to better cope with heat stress (University of Connecticut 2018). Acclimatization is a relatively rapid process, with 75-80% of the physiological adaptations taking place in the first four to seven days (Périard, Racinais, and Sawka 2015).

Along with physiological adjustments to heat, individuals may not perceive hot weather as a health threat, and therefore not have high temperatures impact their activity. For one, the elderly – a demographic that has an elevated risk of heat-related illness – have been found to not consider themselves vulnerable to, or threatened by, heat (Wolf, Adger, and Lorenzoni 2010). Portions of the population may only respond to broadcast heat warnings, such as those during heat wave events, rather than less advertised, singular hot days. Alternatively, those individuals who perceive hot weather as a barrier to activity and utilize weather information to inform their activity decisions may not have accessed weather information altogether, or accessed weather information that disagrees with weather conditions at their location.

Furthermore, the steady increase in average global (and US) temperatures over the past few decades (Section 1.1) may have caused individuals to adjust their behavior to coexist with hotter temperatures, such as shifting physical activity to morning or evening (i.e., the cooler portions of the day), seeking cooler spaces (e.g., parks) for physical activity, avoiding hot spots (e.g., asphalt running tracks), and by wearing lightweight, light-colored, and loose-fitting clothing during activity.

Another possibility for why hot days did not exhibit a significant association with physical activity is that individuals' patterns of activity through the week may be largely set. For 2017, the US Bureau of Labor Statistics found employed men and women averaged 8.7 and 7.7 hours per day, respectively, engaging in work and work-related activities. With limited time available outside of work and other obligations, individuals may not have the luxury to schedule exercise during what he or she perceives as ideal weather conditions, but instead must settle for exercising, if at all, within the small pockets of available leisure time; in 2017, leisure time averaged about 5.5 hours per day for men and 5.0 hours for women, of which an average of 21 minutes and 13.8 minutes, respectively, were devoted to sports, exercise, and recreation (US Bureau of Labor Statistics 2018). These few minutes participating in sports, exercise, and recreation may be more closely tied with prior scheduled arrangements (e.g., activities with friends, fitness classes, dog walking, or an evening jog) rather than with the heat index.

The occupation of an individual may influence physical activity patterns and exposure to hazardous heat. Outdoor occupations that are physically demanding (e.g., construction workers) may have no choice but to perform physical activity in hot conditions, while if those who have indoor, mostly sedentary occupations (e.g., office worker) elect to exercise, then they have little choice but to exercise before or after work during the cooler portions of the day. If weekends are without work, individuals may decide to exercise as compensation for their dearth of weekday activity, and/or decide to recover from their physically demanding work week.

Of the above overview of potential reasons for summer heat not exhibiting a significant association with physical activity, only heat acclimatization, behavioral adjustments for thermal comfort, and activity patterns that intentionally or unintentionally separate physical activity from the hottest parts of the day, remove individuals from hot weather conditions. While model predictions for Question 1 provide evidence that summer heat may not induce physical inactivity, these results suggest that individuals may be vulnerable to heat-related health outcomes (Section 7.2).

The research design and methodology for Question 1 have limitations – shared by the other two central research questions – that can be rectified in future work. First, the relatively small sample size (i.e., 134 individuals for dependent variable Any Activity and 117 individuals for dependent variable Recommended Activity) reduces statistical power and increases the likelihood of Type II errors. To remediate, future research should increase the number of study participants per city, which will increase the ability to find a statistical effect in the sample if the effect exists in the population and reduce the likelihood of false negative outcomes.

Second, while growth curve models for the central research questions control for demographic characteristics (i.e., sex, race, age, health, income, and city of residence), this work does not run separate models based on different population subgroups. According to past US surveillance of physical activity behavior, younger, White, non-Hispanic men are more likely to meet national physical activity guidelines than other populations (Haskell et al. 2007), and because of this, could have been evaluated separately from other populations. In addition, previous work categorizes individuals into typologies based on physical activity behavior, such as the active couch potato (i.e., an individual with high sedentary time and physical activity – someone who bikes to work, but then who works all day at a desk and later watches television in the evening) (Owen et al. 2010). Future research could increase the overall number of study participants and run separate growth curve models after stratifying the sample by both demographic characteristics related to physical activity and physical activity typologies.

Third, this work relies on self-reported TADs to develop the dependent variable. TADs are subjective measures of physical activity, which limits reliability and validity for reasons including misinterpretation of directions, accidental input errors, recall bias, and response bias (Shephard 2003). Moreover, participants may record inflated physical activity levels when performing physical activity in hot and humid conditions because of thermal discomfort – a symptom rather than the behavior itself. A systematic review found self-reported measures of physical activity were both higher and lower than direct measures of physical activity (Prince et al. 2008).

In lieu of self-reported TADs, future work could make use of accelerometers and global positioning systems (GPS) to develop the physical activity variable. Accelerometers are electronic, wearable, activity monitors that directly measure physical activity intensity at programmable time intervals with proven reliability and validity (Prince et al. 2008, O'Neil et al. 2016, Aadland and Ylvisåker 2015). By outfitting each study participant with an accelerometer and GPS, the study would be able to capture a high-quality measure of physical activity at an exact time and place, allowing for stratification into outdoor, indoor, and total physical activity. However, accelerometers are not without limitations, as these devices are 1) potentially cost prohibitive, 2) able to malfunction, 3) variable in reliability and validity across brands, 4) unable to measure upper body physical activity because of placement on hip, and 5) unable to measure whether carrying weight (Lee and Shiroma 2013).

Fourth, the use of heat index to define hot days and heat waves is problematic for physical activity research because other weather elements, in addition to air temperature and relative humidity, impact heat stress in humans. Future research should define hot days and heat waves using a temperature metric commonly utilized by the US military and in athletics: wet bulb globe temperature (WBGT). WBGT is an index of heat stress that combines the measures of air temperature, relative humidity, wind speed, and solar radiation (i.e., sun angle and cloud cover). WBGT is intended to measure heat stress in direct sunlight, unlike heat index, which is intended to measure heat stress in shady areas (US National Oceanic and Atmospheric Administration 2018b). This work used heat index instead of WBGT to define hot days and heat waves because most weather stations in the US, including those used in this study, are unable to compute WBGT because they do not measure solar radiation – one of the four inputs for WBGT.

Future work should identify which weather stations across a city measure WBGT, and if none, then purchase a WBGT heat stress meter for the study. Instead of defining hot days and heat waves from a single airport weather station per city, future work could improve the validity of heat measurements by using the WBGT values from the weather station or WBGT heat stress meter closest to each study participant's home. Lastly, future research can assess how different definitions of hot days and heat waves impact physical activity levels. Hot days and heat waves can be defined by different percentile thresholds of maximum, minimum, and/or average WBGT, and heat waves can also be defined by different number of days.

Fifth, developing the focal predictor of interest (i.e., hot days) from the maximum daily heat index assumes that 1) individuals base their physical activity decisions on forecasted high temperatures, 2) other hours outside of peak temperature periods on hot days also exhibit higher than usual temperatures, and/or 3) individuals did not shift physical activity to cooler periods on hot days. Instead of exploring the association between heat index and physical activity across days, future research could examine how heat index and its fluctuations throughout the day impacts when an individual participates in physical activity.

4.5 Conclusion

This chapter detailed Question 1, the first of three central research questions in this work: How do hot days associate with outdoor, indoor, and total physical activity behavior across all active living domains? In particular, this chapter overviewed the knowledge gap in the literature, research sub-questions and hypotheses, methods specific to these questions, output from statistical models, interpretation of results, limitations of the research design, and possible solutions to these limitations in future work. The major takeaway is that hot days do not exhibit significant associations with outdoor, indoor, and total physical activity. The chapter did not cover the implications of this finding or recommendations for practice, which will be covered at length in Chapter 7. But first, this work will continue with the next two central research questions.

CHAPTER 5. HOT DAYS, BUILT ENVIRONMENT, AND PHYSICAL ACTIVITY

5.1 Introduction

As illustrated in Section 3.2.2, this chapter covers Question 2: How do hot days influence the effect of built environment factors on outdoor physical activity behavior across all active living domains? This central research question is of direct interest to city and regional planners, professionals who have the motivation, skillset, and local jurisdiction to design areas for community improvement. To combat sprawl – a pattern of low-density, dispersed, segregated, automobile-dependent, urban-fringe development – many planners advocate for Smart Growth – a pattern characterized by compact, mixed, multi-modal development that helps "protect our health and natural environment and make our communities more attractive, economically stronger, and more socially diverse" (US Environmental Protection Agency 2018).

In addition to associating with Smart Growth's commitment of protecting human health, Question 2 directly relates to one of the ten principles of Smart Growth: Create walkable neighborhoods (US Environmental Protection Agency 2018). Research shows that several aspects of the environment may encourage physical activity, including walking, at the neighborhood level: Characteristics of the built environment (e.g., density, safety, trees, and hilliness) and access to behavior settings (e.g., connectivity, access to parks, and access to shops + services) exhibit significant associations with physical activity (Section 2.4).

However, how aspects of the built environment impact physical activity may be influenced by heat, a common trait of urban areas during the summer. Numerous studies have evaluated the associations between temperature and/or built environment factors with physical activity (Barnett et al. 2017, Cain et al. 2014, Cerin et al. 2017, Tucker and Gilliland 2007, Wang et al. 2016), but a search of the literature found no studies assessed whether heat influences the effect of built environment factors on outdoor physical activity. Heat may interact with both characteristics of the built environment and access to behavior settings, potentially resulting in a change in effect size of these factors on physical activity than if the interactions were not modeled.

Specifically, Question 2 examines the impact on outdoor physical activity of the interaction between hot days and seven built environment factors: 1) density, 2) safety, 3) trees, 4) hilliness, 5) connectivity, 6) access to parks, and 7) access to shops + services. Built environment factors 1-4 relate to characteristics of the built environment, and factors 5-7 relate to access to behavior settings. The overarching hypothesis for Question 2 is that hot days will increase the magnitude of the expected directional effect of all built environment factors on outdoor physical activity levels (i.e., safety, trees, connectivity, access to parks, and access to shops + services will have more positive associations with physical activity levels on hot days, while density (as mean block size) and hilliness will have more negative associations). For example, if an increase in tree canopy increases physical activity levels, then on hot days, that same increase in tree canopy will result in an even larger increase in physical activity.

5.2 Method Details

After the removal of study days missing ≥ 30% TAD data and for those individuals who participated in zero total physical activity across all study days, the study sample included 134 adults and 741 days for dependent variable Any Activity and 117 adults and 717 days for dependent variable Recommend Activity. While Chapter 3 outlines the methods shared by the three central research questions, the remainder of this section describes the methods specific to Question 2; the one exception being that Question 1 and 2 share study days defined as hot days (Figure 14).

Of the seven built environment factors of interest to this study, the 3HEAT project only measured the 'safety' variable, the lone built environment factor within the Perceived Environment level of the Ecological Model (Figure 7). This study selected the remaining six factors based on literature finding statistically significant associations with physical activity and availability as secondary data from government sources across all three cities. These six built environment variables were formatted as vector or raster image files, and analyzed within a geographic information system (ESRI ArcGIS, version 10.5.1). Unique to the Atlanta sample, 14 of the 57 study participants lived in Cobb County, which is outside city boundaries but within the metropolitan region. Therefore, three variables (i.e., connectivity, access to parks, and access to shops + services) required data supplementation to cover the spatial extent of the Atlanta study households.

This study assessed all built environment factors within an 800m radius from a participant's home address. The literature commonly adopts a distance (e.g., 400m, 800m, or 1,600m) from a location to capture the local environment in which an individual may pursue a significant portion of physical activity (McCormack and Shiell 2011), with 800m equating to approximately a 10-minute walk from a location (Azmi, Karim, and Amin

2012, Harrison et al. 2011, Ker and Ginn 2003). In this work, GIS was utilized to 1) geocode participants' home addresses as vector point Shapefiles, 2) process each of the built environment factors, and 3) clip the built environment factors using an 800m Euclidean buffer with the buffer centroid as each study participant's home address.

For the 'density' variable, mean census block size of an area served as a proxy for population density, with an inverse relationship between block size and density. To develop the 'density' variable, this study made use of TIGER/Line Shapefiles of census blocks (vector polygons) in Arizona, Georgia, and Michigan (US Census Bureau 2016a). Within GIS, the area (acres) of each census block was calculated; an 800m Euclidean buffer was used to remove all census blocks beyond 800m of each participant's home address; and the mean block size was computed for the remaining census blocks in proximity to each participant's address.

The 'safety' variable – the only built environment factor in this study collected by 3HEAT and not requiring processing within GIS – originated from a screening survey administered to all Phase I study participants. The survey item was an attempt to understand an individual's perceived neighborhood safety by asking, "How safe or unsafe do you feel in your neighborhood?," with four possible answers for level of safety: 1) very unsafe, 2) somewhat unsafe, 3) somewhat safe, and 4) very safe. To develop the final 'safety' variable (defined as safe = 0 and unsafe = 1) safety levels 3-4 were recoded as a value of "0" and safety levels 1-2 were recoded as a value of "1."

The 'trees' variable measured the percent coverage of tree canopy within 800m of each participant's home by utilizing aerial imagery (one-meter, four-band raster images) provided by the National Agriculture Imagery Program at a relatively low cost (US Department of Agriculture n.d.). The aerial images were captured during the agricultural growing season – the period of peak vegetative health that matches the vegetative conditions during study days – in 2015, 2014, and 2013 for Atlanta, Detroit, and Phoenix, respectively. To calculate the 'trees' variable, aerial imagery and a city boundary Shapefile (vector polygon) were imported into GIS. A mosaic of aerial images for each city served as the input raster file for unsupervised image classification within an image processing program (ERDAS IMAGINE, 2015). The unsupervised classification utilized k-means clustering to categorize pixels into 100 unique classes, which were then reclassified within GIS into either 0) non-tree or 1) tree. Zonal statistics were employed to calculate the percentage of pixels for each census tract occupied by tree canopy.

The 'hilliness' variable measured the mean slope of the ground in degrees (i.e., 0˚ = flat surface and 90˚ = completely vertical surface), using 1/3 arc-second digital elevation models (10-meter raster images) provided by the National Elevation Dataset for Atlanta, Detroit, and Phoenix (US Geological Survey 2017). Within GIS, a raster image of slope values in degrees was computed from each digital elevation model using the Slope tool within the Spatial Analyst toolbox of ArcGIS. To arrive at the final mean slope of the surface within 800m of each participant's home address, zonal statistics were computed from the raster image of slope values and the 800m Euclidean buffer that associated with each participant's address.

For the 'connectivity' variable, the number of road intersections in an area served as a proxy for connectivity – the ability to access different destinations. To develop the 'connectivity' variable, this study made use of TIGER/Line Shapefiles of all roads (vector line) for the counties affiliated with Atlanta (Dekalb and Fulton), Detroit (Wayne), and Phoenix (Maricopa) (US Census Bureau 2016b). For the 14 participants who lived outside of Atlanta city boundaries, TIGER/Line Shapefiles of all roads affiliated with Cobb County were used. Within GIS, the following road types – categorized by MAF/TIGER Feature Class Code – were removed because of their inaccessibility for physical activity: S1100 (primary), S1500 (vehicular traffic – 4WD), S1630 (ramp), S1640 (scenic drive along limited access highway), S1730 (alley for deliveries), S1740 (private road for service vehicles), and S1750 (internal US Census Bureau use). After removal, the following road types remained to develop the 'connectivity' variable: S1200 (secondary), S1400 (local neighborhood, urban street), S1710 (walkway/pedestrian trail), S1780 (parking lot road), and S1820 (bike path or trail). From these remaining roads, intersections were computed, and then the number of road intersections were counted within 800m of each participant's home address.

The 'access to parks' variable measured the total area (acres) of public parks within 800m of each participant's home address, using local data sources for each city. For Atlanta, data originated from both a Parks Shapefile (vector polygon) and a Greenspace Shapefile (vector polygon), with the spatial extent of the former being Atlanta city boundaries and of the latter being the Atlanta region (City of Atlanta 2018a, Atlanta Regional Commission 2018). The two Shapefiles were combined and duplicate parks, as well as greenspaces not listed as "Public Park" or "Municipal Park," were removed. For Detroit, data originated from a Parks and Landmarks Shapefile (vector polygon), with all items not listed as "Park" removed (Data Driven Detroit 2018). For Phoenix, data originated from a Park Boundary Shapefile (vector polygon), with public park types (i.e., basin, community, desert park, district, mini, and neighborhood) maintained and non-public park types (i.e., golf, mountain preserved, special area, and undeveloped) removed (City of Phoenix 2018a). After trimming the Shapefiles to only public parks for each city, 800m Euclidean buffers were used to clip the portion of a park found within 800m of a participant's home address. The sum of these clipped park portions constituted the final value for the 'access to parks' variable. This work chose to clip the park portions that intersected and were outside the buffer to control for the overall size of the park. For example, individuals may only frequent those portions of very large parks that are closer to their home address.

The 'access to shops + services' variable measured the number of commercial properties within 800m of each participant's home address by utilizing parcel Shapefiles (vector polygon) for each study city (City of Atlanta 2018b, City of Detroit 2015, City of Phoenix 2018b). Property use codes for each parcel included within the parcel Shapefiles were used to identify commercial properties from other property types, but the Atlanta Shapefile was missing property use code data for parcels within Dekalb County, and the Phoenix Shapefile did not include property use codes. To have complete property use code data for Atlanta and Phoenix, this work obtained property tax digests for Dekalb County and Maricopa County, respectively, and joined these data to the parcel Shapefiles (DeKalb County Property Appraisal Department 2016, Arizona State University 2014). From the Detroit parcels and the updated Atlanta and Phoenix parcel Shapefiles, the number of commercial shops and services were counted within 800m of each participant's home address. For the 14 Atlanta study participants who lived outside city boundaries, this work used Google Maps, as well as the Circles tool for Google Maps to draw 800m Euclidean buffers, to count the number of commercial properties within 800m of each participant's address.

Descriptive statistics were conducted for all predictor variables on Level 1 of study day and Level 2 of study individual (Table 9), as well as for the two dependent variables of daily percentage of outdoor physical activity from the two versions of the dependent variable (i.e., Any Activity and Recommended Activity). To understand how hot days influence the effect of built environment factors on outdoor physical activity, separate two-level growth curve models were run for each of the two dependent variables within SPSS.

Table 9. Predictor variables included in growth curve models (Question 2).

Variable	Metric	Source
	Level 1 Time-Varying Variables	
WEATHER		
Hot day	≥ 90th percentile of max daily heat index (°F)	US National Oceanic and Atmospheric Administration (2018b)
Rainy day	daily precipitation (yes/no)	US National Oceanic and Atmospheric Administration (2018b)
TIME		
Weekend day	weekend (yes/no)	3HEAT (2016)
	Level 2 Time-Invariant Variables	
INDIVIDUAL		
Sex	female (yes/no)	3HEAT (2016)
Race	Non-White (yes/no)	3HEAT (2016)
Age[1]	years	3HEAT (2016)
Health	perceived not good health (yes/no)	3HEAT (2016)
Income	annual household income ($)	3HEAT (2016)
ENVIRONMENT		
Density	mean block size (acres) w/in 800m of home	US Census Bureau (2016a)
Safety	perceived neighborhood unsafe (yes/no)	3HEAT (2016)
Trees	% tree canopy w/in 800m of home	US Department of Agriculture (n.d.)
Hilliness	mean slope (degrees) w/in 800m of home	US Geological Survey (2017)
Connectivity	# of road intersections w/in 800m of home	US Census Bureau (2016b)
Access to parks	area (acres) of parks w/in 800m of home	Atlanta Regional Commission (2018), City of ATL (2018), City of PHX (2018), Data Driven Detroit (2018)
Access to shops + services	# of comm. properties w/in 800m of home	City of ATL (2018b) City of DET (2015), City of PHX (2018b)
CITY		
Detroit[2]	Detroit (yes/no)	3HEAT (2016)
Phoenix[2]	Phoenix (yes/no)	3HEAT (2016)
	Level 2 Cross-Level Interactions	
ENVIRONMENT		
Hot day*Density[3]		
Hot day*Safety[3]		
Hot day*Trees[3]		

Hot day*Hilliness[3]	
Hot day*Connectivity[3]	
Hot day*Access to parks[3]	
Hot day*Access to shops + services[3]	

[1]Age variable was mean-centered to aid interpretability and protect against multicollinearity.

[2]Omitted category = Atlanta.

[3]See single terms for metrics and sources of interaction terms. Built environment term of interaction term was mean-centered.

To arrive at the full growth curve model, this analysis included a succession of three growth curve models (Models 1-3), where each model built off the previous model: Model 1 was the unconditional growth model with dependent variable, time indicator variable, and intercepts; Model 2 added hot day, rainy day, density, safety, trees, hilliness, connectivity, access to parks, and access to shops + services; and Model 3 added weekend day, sex, race, age, health, income, Detroit, and Phoenix. If both hot day and a built environment factor were found to be significant in Model 2, then Model 3 would include cross-level interaction terms (i.e., hot day*density, hot day*safety, hot day*trees, hot day*hilliness, hot day*connectivity, hot day*access to parks, and hot day*access to shops + services). The Level 1, Level 2, and Mixed formulas for the proposed final model are displayed below (Equation 7):

(Level 1)

$$PhysicalActivity_{ti} = \pi_{0i} + \pi_{1i} * Time_{ti} + \pi_{2i} * HotDay_{ti} + \pi_{3i} * RainyDay_{ti} + \pi_{4i} * WeekendDay_{ti} + e_{ti}$$

(Level 2)

$$\pi_{0i} = \beta_{00} + \beta_{10} * Sex_i + \beta_{20} * Race_i + \beta_{30} * Age_i + \beta_{40} * Health_i + \beta_{50} * Income_i + \beta_{60} * City_i + \beta_{70} * Density_i + \beta_{80} * Safety_i + \beta_{90} * Trees_i + \beta_{10\,0} * Hilliness_i + \beta_{11\,0} * Connectivity_i + \beta_{12\,0} * Parks_i + \beta_{13\,0} * Shops_i + r_{0i} \quad \text{(Equation 7)}$$

$$\pi_{1i} = \beta_{10}$$

$\pi_{2i} = \beta_{20}$

$\pi_{3i} = \beta_{30}$

$\pi_{4i} = \beta_{40}$

(Mixed)

$$\begin{aligned} PhysicalActivity_{ti} &= \beta_{00} + \beta_{10} * Sex_i + \beta_{20} * Race_i + \beta_{30} \\ &* Age_i + \beta_{40} * Health_i + \beta_{50} * Income_i \\ &+ \beta_{60} * City_i + \beta_{70} * Density_i + \beta_{80} \\ &* Safety_i + \beta_{90} * Trees_i + \beta_{10\,0} * Hilliness_i \\ &+ \beta_{11\,0} * Connectivity_i + \beta_{12\,0} * Parks_i \\ &+ \beta_{13\,0} * Shops_i \\ &+ \beta_{10} * Time_{ti} + \beta_{20} * HotDay_{ti} + \beta_{30} \\ &* RainyDay_{ti} + \beta_{40} * WeekendDay_{ti} + r_{0i} \\ &+ e_{ti} \end{aligned}$$

5.3 Results

Table 10 reports the pooled three-city descriptive statistics for all model variables on Levels 1 and 2. Section 4.3 summarizes the pooled and city-specific descriptive statistics for all variables except for the seven built environment variables unique to Question 2. With no official benchmarks for levels of built environment factors, a comparative analysis of descriptive statistics per city aids understanding of the magnitude of the built environment variables (APPENDIX C. descriptive statistics per City). Among built environment variables that correspond to characteristics of the built environment, the Detroit sample had the highest density, i.e., the smallest mean block size (11.8 acres), within 800m of the home of the three cities, followed by Phoenix and Atlanta. In Detroit, the largest percentage of individuals (11.6%) perceived the neighborhood as unsafe, followed by Phoenix and Atlanta. Regarding tree canopy within 800m of the home, the Atlanta sample (42.9%) had almost three times more tree canopy than Detroit, and more than four times as much canopy as Phoenix. In terms of hilliness within 800m of the home, Detroit and Phoenix were close to flat, while Atlanta was hilly, with an average slope of 4.8 degrees.

Among built environment variables that correspond to access to behavior settings, study participants in Atlanta lived in areas with the greatest connectivity, as shown by averaging 243.2 road intersections within 800m of the home, about 20 more intersections than found in the Detroit and Phoenix samples. The Detroit sample had access to the greatest amount of park acreage (36.5) within 800m of home, about 1.5 times and four times greater park access than in Atlanta and Phoenix, respectively. On average, the Phoenix sample had access to the most shops and services (144.2 commercial properties) within 800m of the home, followed closely by Detroit, with Atlanta having the lowest access.

Table 10. Pooled three-city descriptive statistics (Question 2).

Variable	Count	% of Total	Mean	Standard Deviation
Level 1 Time-Varying Variables[1]				
PHYSICAL ACTIVITY				
Any activity, outdoor (%)			6.8	11.0
Any activity, indoor (%)			40.8	28.1
Any activity, total (%)			47.5	28.1
Recommended activity, outdoor (%)			3.6	8.7
Recommended activity, indoor (%)			8.0	15.4
Recommended activity, total (%)			11.6	17.5
WEATHER				
Heat index (°F)			95.7	8.5
Hot day	322	43.5		
Rainy day	203	27.4		
TIME				
Weekend day	178	24.0		
Level 2 Time-Invariant Variables[2]				
INDIVIDUAL				
Sex (female)	87	64.9		
Race (Non-White)	70	52.2		
Age (years)			44.9	16.6
Health (not good health)	35	26.1		
Income ($)			65,130	59,388
ENVIRONMENT				
Density (mean block size, acres)[3]			18.8	40.7

Safety (neighborhood unsafe)	10	7.5		
Trees (% canopy)[3]			22.6	20.3
Hilliness (mean slope, degrees)[3]			2.3	2.3
Connectivity (# road intersections)[3]			230.1	82.7
Access to parks (acres)[3]			24.0	39.0
Access to shops + services (# comm.)[3]			136.2	94.6

[1]Based on 741 days from dependent variable Any Activity (i.e., physical activity defined as intensity levels 2-4). Dependent variable Recommended Activity (i.e., physical activity defined as intensity levels 3-4) removes 24 days across the three cities.

[2]Based on 134 individuals from dependent variable Any Activity (i.e., physical activity defined as intensity levels 2-4). Dependent variable Recommended Activity (i.e., physical activity defined as intensity levels 3-4) removes 17 individuals across the three cities.

[3]Within 800m of each study participant's home address.

This work focused on the model output for dependent variable version Any Activity (Table 11) over Recommended Activity (APPENDIX E. Results: How hot days influence the effect of built environment factors on outdoor physical activity (Recommended Activity)), because the former had less study days (i.e., 41%) with zero outdoor physical activity than the latter (i.e., 68%), resulting in improved data distribution. However, the model output for both versions Any Activity and Recommended Activity showed equal significance of association between focal predictors and activity. Within the three-model set for Any Activity outdoor, this analysis reported on Model 3 because this final, most elaborate model had the best fit over Models 1 and 2, as determined by an increased reduction in τ_{00}, along with decreasing values for AIC and BIC.

For outdoor physical activity (Table 11), Model 3 accounted for 4.91% of the variance of the intercept (Level 2), and the statistically significant value for the unexplained variance at baseline indicates that there are other, omitted factors that can explain outdoor physical activity. Model 3 accounted for 11.2% of the within group (Level 1) variance, with the remaining variance not found to be statistically significant. Model 3 estimated that hot day ($\beta = 0.01$, $p = 0.94$); density ($\beta = -0.01$, $p = 0.27$); safety ($\beta = -0.17$, $p = 0.62$); trees ($\beta = 0.01$, $p = 0.80$); hilliness ($\beta = -0.07$, $p = 0.46$); connectivity ($\beta = 0.01$, $p = 0.81$); access to parks (β = -0.01, p = 0.78); and access to shops + services (β = -0.01, p = 0.38) did not have significant associations with the log of daily percentage of outdoor physical activity, holding all other variables constant. The final model omitted interaction terms, the focal predictors of Question 2, because neither of the main effects (i.e., hot day and any given built environment factor) were statistically significant on their own.

Among control variables, Model 3 predicted that being female associated with a 36% decrease in the log of daily percentage of outdoor physical activity (p = 0.09). Lastly, the model predicted that being not in good health corresponded with a 38% decrease in the log of daily percentage of outdoor physical activity (p = 0.09). All other model variables exhibited insignificant associations with the log of daily percentage of outdoor physical activity (p > 0.10).

Table 11. Model results: How hot days influence the effect of built environment factors on outdoor physical activity.

	Model 1	Model 2	Model 3
Fixed effects			
Intercept	1.30^{***}	1.38^{***}	2.24^{**}
Level 1-time-varying variables			
Weather			
Hot Day (0 = not hot day)		-0.04	0.01
Rainy Day (0 = not rainy day)		-0.08	-0.13
Weekend Day (0 = not weekend day)			-0.01
Level 2-time-invariant variables			
Individual			
Sex (0 = male)			-0.36^{*}
Race (0 = White)			-0.32
Age (0 = 44.9 years)[1]			-0.01
Health (0 = good health)			-0.38^{*}
Income ($)			0.01
City of Residence[2]			
Detroit (0 = not Detroit)			-0.17
Phoenix (0 = not Phoenix)			-0.39
Environment			
Density (mean block size, acres)[3]		-0.01	-0.01
Safety (0 = neighborhood safe)		-0.14	-0.17

Trees (% canopy)[3]		0.01	0.01
Hilliness (mean slope, degrees)[3]		0.01	-0.07
Connectivity (# road intersections)[3]		-0.01	0.01
Access to parks (acres)[3]		-0.01	-0.01
Access to shops + services (# comm.)[3]		-0.01	-0.01
Random effects			
τ_{00} (intercept)	0.57***	0.60***	0.57***
σ^2	0.04	0.03	0.03
Model fit			
Reduction in τ_{00}		-5.95 %	4.91 %
Reduction in σ^2		30.4 %	11.2 %
AIC	2,265.6	2,199.0	1,798.4
BIC	2,279.4	2,212.6	1,811.4

Dependent variable: log of daily percentage of outdoor physical activity, Any Activity.
* p < 0.10 ** p < 0.05 *** p < 0.01

[1]Age variable was mean-centered to aid interpretability and protect against multicollinearity.

[2]Omitted category = Atlanta.

[3]Within 800m of each study participant's home address.

5.4 Discussion

The final growth curve models found that hot days – days ≥ 90th percentile of maximum daily heat index – did not significantly influence the effect of built environment factors on outdoor physical activity of adults. These results do not corroborate with the stated hypotheses. Hot days did not increase the positive association between built environment factors (i.e., safety, trees, connectivity, access to parks, and access to shops + services) and outdoor physical activity, or increase the negative association between built environment factors (i.e., density as mean block size and hilliness) and outdoor physical activity. Moreover, the models found hot days and the seven built environment factors did not independently exhibit significant associations with outdoor physical activity, the former of which exhibits mixed associations in the literature (Section **Error! Reference source not found.**), and the latter of which exhibits more unidirectional associations (Section 2.4). Overall, these results may imply that cities should focus on other environmental characteristics when aiming to increase population-level physical activity. Chapter 7 will further discuss the implications of the Question 2 findings and detail how changes to the built environment can reduce temperatures, as well as potentially encourage physical activity.

During hot weather, individuals may not be actively 1) seeking those built environment factors that exhibit positive associations in the literature (i.e., safety, trees, connectivity, access to parks, and access to shops + services) or 2) avoiding those built environment factors that exhibit negative associations in the literature (i.e., density as mean block size and hilliness), potentially due to the five reasons outlined in Section 4.4: 1) high behavioral threshold to heat due to acclimatization, 2) heat not perceived as a health threat, 3) lack of access to weather information altogether or accurate weather information, 4) behavioral adjustments to heat, and 5) inflexible schedules.

The research design and methodology for Question 2 shares the five limitations outlined for Question 1 (Section 4.4). Another limitation of Question 2 is in the design of six of the built environment factors (i.e., Density, Trees, Hilliness, Connectivity, Access to parks, and Access to shops + services). By restricting these built environment variables to within an 800m distance of participants' home addresses, this work assumes outdoor physical activity of study participants took place near the home. In reality, individuals may choose to be physically active outside of this near-home environment, such as bike commuting more than 800m from home to the workplace; the built environment variables in current form would not capture the environmental characteristics past 800m.

To understand if this limited distance for the built environment variables is an issue, future work can assess whether there is significant difference between outputs of growth curve models using built environment variables calculated at 400m, 800m, and 1,600m from each participant's home address, which correspond to five-minute, 10-minute, and 20-minute walks, respectively. To release this research question from the distance limitation altogether, each study participant can be followed across space with GPS, allowing for development of built environment factors using the precise location of study participants. Using GPS would allow the built environment variables to better capture what each is meant to capture. For example, instead of the 'trees' variable quantifying all canopy within 800m of a home address, GPS would permit researchers to select only the tree canopy within the sight lines of study participants, not tree canopy hidden from view (e.g., residential backyard trees) that may not directly influence an individual's physical activity if not on his or her property.

5.5 Conclusion

This chapter detailed Question 2, the second of three central research questions in this work: How do hot days influence the effect of built environment factors on outdoor physical activity behavior across all active living domains? In particular, this chapter overviewed the knowledge gap in the literature, research sub-questions and hypotheses, methods specific to these questions, output from statistical models, interpretation of results, limitations of the research design, and possible solutions to these limitations in future work. The major takeaway is that hot days did not significantly influence the effect of built environment factors on outdoor physical activity of adults. The chapter did not cover the implications of this finding or recommendations for practice, which will be covered at length in Chapter 7. But first, this work will continue with the last central research question.

CHAPTER 6. HEAT WAVES AND PHYSICAL ACTIVITY

6.1 Introduction

As illustrated in Section 3.2.3, this chapter covers Question 3: How do heat waves associate with outdoor, indoor, and total physical activity behavior across all active living domains? Heat waves – broadly defined as consecutive days of excessively high temperatures – have been documented as one of the deadliest natural disasters because prolonged exposure to extreme heat, without any cooling relief, can physiologically overstress an individual's thermoregulatory system and potentially lead to death. During a seven-day heat wave in Chicago in July 1995, researchers attributed 739 excess deaths to heat, when comparing the total number of deaths from all causes with the long-term average of daily deaths (1979-1994) for this same time period (Whitman et al. 1997). Based on a similar analysis for a regional-level heat wave across Europe in 2003, researchers attributed more than 70,000 excess deaths to heat, when comparing the total deaths in summer 2003 with the long-term average (1998-2002) for 16 countries (Robine et al. 2008).

The literature covers the adverse effects of heat waves on the health outcomes of heat-related morbidity and mortality (Kenney, Craighead, and Alexander 2014). Hatvani-Kovacs et al. (2016) found that the excess heat factor – a metric that quantifies heat wave intensity relative to local climate – explained 77.1% of the excess morbidity ($p < 0.001$) in South Australia. Regarding mortality risk for heat waves in 43 US cities (1987-2005), Anderson and Bell (2011) found that deaths increased 3.74% (95% posterior interval = 2.29–5.22) during heat waves compared with non-heat wave days, and that every 1°F increase in heat wave intensity increased heat wave mortality risk by 2.49% ($p < 0.01$). While heat waves are clearly linked to excess morbidity and mortality, no research addresses the connection between heat waves and the health outcome of physical inactivity; Question 3 investigates this relationship, and if the relationship changes based on outdoor, indoor, and total physical activity.

The three hypotheses for Question 3 have similarities to those of Question 1 (i.e., how hot days associate with outdoor, indoor, and total physical activity). This study posits that each subsequent heat wave day will associate with a larger decrease in outdoor physical activity at an increasing rate over time, as individuals, from direct exposure and/or accessing weather information, are impacted by prolonged thermally uncomfortable conditions. Each subsequent heat wave day will associate with a larger increase in indoor physical activity at an increasing rate over time, as individuals shift their physical activity from outdoor to climate-controlled indoor environments. Lastly, each subsequent heat wave day will associate with a larger decrease in total physical activity at an increasing rate over time, as the decrease in outdoor physical activity each day will not be offset by the increase in indoor physical activity each day.

6.2 Method Details

After the removal of study days missing ≥ 30% TAD data and for those individuals who participated in zero total physical activity across all study days, the study sample included 134 adults and 741 days for dependent variable version Any Activity and 117 adults and 717 days for Recommend Activity. While Chapter 3 outlines the methods shared by the three central research questions, the remainder of this section describes the methods specific to Question 3. Figure 15 shows that 15, eight, and zero study days across Atlanta, Detroit, and Phoenix, respectively, were considered heat wave days (i.e., two or more consecutive days ≥ the 90th percentile of daily maximum heat index during the warm season from 2000-2016).

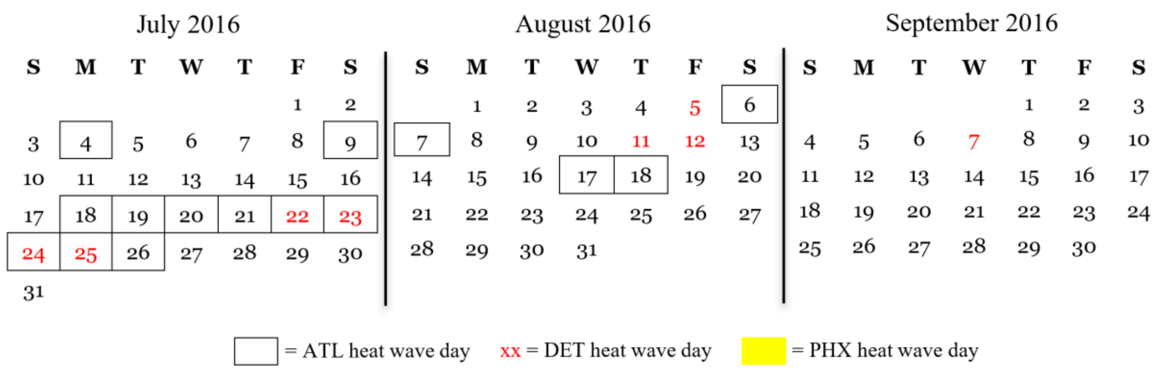

Figure 15. Study days (post data processing) considered heat waves in Atlanta, Detroit, and Phoenix.

Descriptive statistics were conducted for all predictor variables on Level 1 of study day and Level 2 of study individual (Table 12), as well as for the six dependent variables of daily percentage of physical activity from the two versions of the dependent variable (i.e., Any Activity and Recommended Activity) and three physical activity locations (i.e., outdoor, indoor, and total). To understand how heat waves associate with daily percentage of physical activity, separate two-level growth curve models were run for each of the six dependent variables within SPSS.

Table 12. Predictor variables included in growth curve models (Question 3).

Variable	Metric	Source
	Level 1 Time-Varying Variables	
WEATHER		
Heat wave day 2	2nd day of ≥ 90th percentile of max daily heat index (°F)	US National Oceanic and Atmospheric Administration (2018b)
Heat wave day 3+	3rd+ day of ≥ 90th percentile of max daily heat index (°F)	US National Oceanic and Atmospheric Administration (2018b)

Rainy day	daily precipitation (yes/no)	US National Oceanic and Atmospheric Administration (2018b)
TIME		
Weekend day	weekend (yes/no)	3HEAT (2016)
	Level 2 Time-Invariant Variables	
INDIVIDUAL		
Sex	female (yes/no)	3HEAT (2016)
Race	Non-White (yes/no)	3HEAT (2016)
Age[1]	years	3HEAT (2016)
Health	perceived not good health (yes/no)	3HEAT (2016)
Income	annual household income ($)	3HEAT (2016)
CITY		
Detroit[2]	Detroit (yes/no)	3HEAT (2016)
Phoenix[2]	Phoenix (yes/no)	3HEAT (2016)

[1]Age variable was mean-centered to aid interpretability and protect against multicollinearity.

[2]Omitted category = Atlanta.

To arrive at the full growth curve model, this analysis included a succession of three growth curve models (Models 1-3), where each model built off the previous model: Model 1 was the unconditional growth model with dependent variable, time indicator variable, and intercepts; Model 2 added heat wave day 2, heat wave day 3+, and rainy day; and Model 3 added weekend day, sex, race, age, health, income, Detroit, and Phoenix. The Level 1, Level 2, and Mixed formulas for the proposed final model are displayed below (Equation 8):

(Level 1)

$$\begin{aligned} PhysicalActivity_{ti} &= \pi_{0i} \\ &+ \pi_{1i} * Time_{ti} + \pi_{2i} * HWDay2_{ti} + \pi_{3i} \\ &* HWDay3_{ti} + \pi_{4i} * RainyDay_{ti} + \pi_{5i} \\ &* WeekendDay_{ti} + e_{ti} \end{aligned}$$

(Equation 8)

(Level 2)

$$\begin{aligned} \pi_{0i} = \beta_{00} + \beta_{10} * Sex_i + \beta_{20} * Race_i + \beta_{30} * Age_i + \beta_{40} \\ * Health_i + \beta_{50} * Income_i + \beta_{60} * City_i \\ + r_{0i} \end{aligned}$$

$$\pi_{1i} = \beta_{10}$$

$$\pi_{2i} = \beta_{20}$$

$\pi_{3i} = \beta_{30}$
$\pi_{4i} = \beta_{40}$

(Mixed)

$$PhysicalActivity_{ti} = \beta_{00} + \beta_{10} * Sex_i + \beta_{20} * Race_i + \beta_{30} * Age_i + \beta_{40} * Health_i + \beta_{50} * Income_i + \beta_{60} * City_i + \beta_{10} * Time_{ti} + \beta_{20} * HWDay2_{ti} + \beta_{30} * HWDay3_{ti} + \beta_{40} * RainyDay_{ti} + \beta_{50} * WeekendDay_{ti} + r_{0i} + e_{ti}$$

6.3 Results

Table 13 reports the pooled three-city descriptive statistics for all model variables on Levels 1 and 2. Section 4.3 summarizes the pooled and city-specific descriptive statistics for all variables except for the two heat wave variables unique to Question 3. Of the pooled three-city data, 10.0% of study days were on the 2nd day of a heat wave, and 20.4% of study days were on a heat wave day extending past the 2nd day. Descriptive statistics of the study sample per city (APPENDIX C. descriptive statistics per City) show that Phoenix had zero study days considered heat waves, which means this study did not assess whether heat waves, as defined, associated with outdoor, indoor, total physical activity of adults in Phoenix. Meanwhile in Atlanta and Detroit, heat wave days constituted more than half of all study days and about 15% of all study days, respectively.

Table 13. Pooled three-city descriptive statistics (Question 3).

Variable	Count	% of Total	Mean	Standard Deviation
Level 1 Time-Varying Variables[1]				
PHYSICAL ACTIVITY				
Any activity, outdoor (%)			6.8	11.0
Any activity, indoor (%)			40.8	28.1

Any activity, total (%)			47.5	28.1
Recommended activity, outdoor (%)			3.6	8.7
Recommended activity, indoor (%)			8.0	15.4
Recommended activity, total (%)			11.6	17.5
WEATHER				
Heat index (°F)			95.7	8.5
Heat wave day 2	74	10.0		
Heat wave day 3+	151	20.4		
Rainy day	203	27.4		
TIME				
Weekend day	178	24.0		
Level 2 Time-Invariant Variables[2]				
INDIVIDUAL				
Sex (female)	87	64.9		
Race (Non-White)	70	52.2		
Age (years)			44.9	16.6
Health (not good health)	35	26.1		
Income ($)			65,130	59,388

[1]Based on 741 days from dependent variable Any Activity (i.e., physical activity defined as intensity levels 2-4). Dependent variable Recommended Activity (i.e., physical activity defined as intensity levels 3-4) removes 24 days across the three cities.

[2]Based on 134 individuals from dependent variable Any Activity (i.e., physical activity defined as intensity levels 2-4). Dependent variable Recommended Activity (i.e., physical activity defined as intensity levels 3-4) removes 17 individuals across the three cities.

This work focused on the model output for dependent variable version Any Activity (Tables 14-16) over Recommended Activity (APPENDIX F. Results: How Heat waves associate with physical activity (Recommended Activity)), because the former had less study days with zero physical activity per physical activity location (i.e., 41% zero outdoor activity, 12% zero indoor activity, and 5% zero total activity) than the latter (i.e., 68% zero outdoor activity, 63% zero indoor activity, and 43% zero total activity), resulting in improved data distribution. However, the model output for both dependent variable versions Any Activity and Recommended Activity showed equal significance of association between focal predictors and activity. Within the three-model sets for Any Activity outdoor, indoor, and total, this analysis reported on Model 3 because this final, most elaborate model had the best fit, as determined by decreasing values for AIC and BIC.

For outdoor physical activity (Table 14), Model 3 accounted for 4.63% of the variance of the intercept (Level 2), and the statistically significant value for the unexplained variance at baseline indicates that there are other, omitted factors that can explain outdoor physical activity. Model 3 accounted for 42.8% of the within group (Level 1) variance, with the remaining variance not found to be statistically significant. Model 3 estimated that the focal predictors of the 2nd day of a heat wave ($\beta = -0.02$, $p = 0.88$) and 3rd plus day of a heat wave ($\beta = -0.04$, $p = 0.77$) did not have significant associations with the log of daily percentage of outdoor physical activity, holding all other variables constant.

Among control variables, Model 3 predicted that being female associated with a 43% decrease in the log of daily percentage of outdoor physical activity ($p = 0.03$). The final model also estimated that being Non-White corresponded with a 36% decrease in the log of daily percentage of outdoor physical activity ($p = 0.08$). Lastly, the model predicted that every one-year increase in age above 44.9 years associated with a 1% decrease in the log of daily percentage of outdoor physical activity ($p = 0.08$). All other model variables exhibited insignificant associations with the log of daily percentage of outdoor physical activity ($p > 0.10$).

Table 14. Model results: How heat waves associate with outdoor physical activity.

	Model 1	Model 2	Model 3
Fixed effects			
Intercept	1.30^{***}	1.31^{***}	1.91^{***}
Level 1-time-varying variables			
Weather			
Heat Wave Day 2 (0 = not heat wave day 2)		-0.06	-0.02
Heat Wave Day 3+ (0 = not heat wave day 3+)		0.08	-0.04
Rainy Day (0 = not rainy day)		-0.09	-0.12
Weekend Day (0 = not weekend day)			-0.01
Level 2-time-invariant variables			
Individual			
Sex (male = 0)			-0.43^{**}
Race (White = 0)			-0.36^{*}
Age (0 = 44.9 years)[1]			-0.01^{*}
Health (0 = not good health)			-0.31
Income ($)			0.01
City of Residence[2]			
Detroit (0 = not Detroit)			0.10

Phoenix (0 = not Phoenix)			-0.25
Random effects			
τ_{00} (intercept)	0.57^{***}	0.57^{***}	0.54^{***}
σ^2	0.04	0.05	0.03
Model fit			
Reduction in τ_{00}		0.64 %	4.63 %
Reduction in σ^2		-11.7 %	42.8 %
AIC	2,265.6	2,271.6	1,749.3
BIC	2,279.4	2,285.4	1,762.3

Dependent variable: log of daily percentage of outdoor physical activity, Any Activity.
* p < 0.10 ** p < 0.05 *** p < 0.01

[1]Age variable was mean-centered to aid interpretability and protect against multicollinearity.

[2]Omitted category = Atlanta.

For indoor physical activity (Table 15), Model 3 accounted for 0.20% of the variance of the intercept (Level 2), and the statistically significant value for the unexplained variance at baseline indicates that there are other, omitted factors that can explain indoor physical activity. Model 3 accounted for -26.0% of the within group (Level 1) variance, with the remaining variance found to be statistically significant. Model 3 estimated that the focal predictors of the 2nd day of a heat wave ($\beta = -1.90$, $p = 0.52$) and 3rd plus day of a heat wave ($\beta = -1.08$, $p = 0.71$) did not have significant associations with daily percentage of indoor physical activity, holding all other variables constant. Among control variables, Model 3 predicted that being female associated with a 9.4% increase in daily percentage of indoor physical activity ($p = 0.06$). All other model variables exhibited insignificant associations with the daily percentage of indoor physical activity ($p > 0.10$).

Table 15. Model results: How heat waves associate with indoor physical activity.

	Model 1	Model 2	Model 3
Fixed effects			
Intercept	42.15^{***}	42.22^{***}	41.70^{***}
Level 1-time-varying variables			
Weather			
Heat Wave Day 2 (0 = not heat wave day 2)		-2.74	-1.90
Heat Wave Day 3+ (0 = not heat wave day 3+)		-1.89	-1.08

Rainy Day (0 = not rainy day)		2.16	2.60
Weekend Day (0 = not weekend day)			-2.09
Level 2-time-invariant variables			
Individual			
Sex (male = 0)			9.36^{*}
Race (White = 0)			-6.87
Age (0 = 44.9 years)[1]			-0.12
Health (0 = not good health)			3.15
Income ($)			-1.31
City of Residence[2]			
Detroit (0 = not Detroit)			5.51
Phoenix (0 = not Phoenix)			1.28
Random effects			
τ_{00} (intercept)	364.69^{***}	363.54^{***}	362.82^{***}
σ^2	0.10^{*}	0.10^{*}	0.13^{**}
Model fit			
Reduction in τ_{00}		0.32 %	0.20 %
Reduction in σ^2		-0.67 %	-26.0 %
AIC	6,758.4	6,745.5	5,286.4
BIC	6,772.2	6,759.3	5,299.5

Dependent variable: daily percentage of indoor physical activity, Any Activity.
* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

[1]Age variable was mean-centered to aid interpretability and protect against multicollinearity.

[2]Omitted category = Atlanta.

For total physical activity (Table 16), Model 3 accounted for 3.10% of the variance of the intercept (Level 2), and the statistically significant value for the unexplained variance at baseline indicates that there are other, omitted factors that can explain total physical activity. Model 3 accounted for -24.4% of the within group (Level 1) variance, with the remaining variance found to be statistically significant. Model 3 estimated that all predictor variables, including the focal predictors of 2nd day of a heat wave ($\beta = -1.84$, $p = 0.53$) and 3rd plus day of a heat wave ($\beta = -0.37$, $p = 0.90$), did not have significant associations with daily percentage of total physical activity ($p > 0.10$), holding all other variables constant.

Table 16. Model results: How heat waves associate with total physical activity.

	Model 1	Model 2	Model 3
Fixed effects			
Intercept	49.35^{***}	49.66^{***}	50.23^{***}

Level 1-time-varying variables			
Weather			
Heat Wave Day 2 (0 = not heat wave day 2)		-3.74	-1.84
Heat Wave Day 3+ (0 = not heat wave day 3+)		-1.15	-0.37
Rainy Day (0 = not rainy day)		1.06	1.07
Weekend Day (0 = not weekend day)			-1.77
Level 2-time-invariant variables			
Individual			
Sex (male = 0)			5.50
Race (White = 0)			-7.11
Age (0 = 44.9 years)[1]			-0.22
Health (0 = not good health)			1.21
Income ($)			-1.19
City of Residence[2]			
Detroit (0 = not Detroit)			8.73
Phoenix (0 = not Phoenix)			2.30
Random effects			
τ_{00} (intercept)	349.41***	350.46***	339.61***
σ^2	0.11*	0.11*	0.13**
Model fit			
Reduction in τ_{00}		-0.30 %	3.10 %
Reduction in σ^2		-0.95 %	-24.4 %
AIC	6,745.6	6,732.9	5,278.9
BIC	6,759.4	6,746.7	5,291.9

Dependent variable: daily percentage of total physical activity, Any Activity.

* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

[1]Age variable was mean-centered to aid interpretability and protect against multicollinearity.

[2]Omitted category = Atlanta.

6.4 Discussion

Similar to the results from Questions 1 and 2, the final growth curve models found that heat waves – two or more consecutive days ≥ 90th percentile of maximum daily heat index – did not have a significant association with daily percentage of outdoor, indoor, and total physical activity of adults. These outcomes do not corroborate with the stated hypotheses. Heat wave periods did not decrease outdoor physical activity levels at an increasing rate over time because of thermally uncomfortable ambient conditions, nor did the lasting heat increase indoor physical activity at an increasing rate over time. The hypothesized shift of physical activity from outdoors to indoors did not materialize. Lastly, heat wave periods did not decrease total physical activity levels at an increasing rate over time. Building on the findings from Question 1, cities need not take hot days – either single or consecutive – into account when developing strategies to promote physical activity of its residents. Section 7.2 discusses how heat waves – events established as deadly for select populations – can have consequences for the physically active.

This research question shares the potential explanations given for the modeled association between hot days and physical activity (Section 4.4): 1) high behavioral threshold to heat due to acclimatization, 2) heat not perceived as a health threat, 3) lack of access to weather information altogether or accurate weather information, 4) behavioral adjustments to heat, and 5) inflexible schedules. Another reason may be that when subjected to consecutive days of extreme heat, individuals may not be able to retain their physical or mental response from the preceding heat wave day, especially if the individual sleeps in an air-conditioned home (which offers relief from heat wave conditions) and did not access weather information throughout the heat wave event. As such, individuals would treat each day within a heat wave the same as a singular hot day, not showing an added response from extended heat exposure, as hypothesized.

The research design and methodology for Question 3 has the same five limitations outlined for Questions 1 and 2 (Section 4.4). Another limitation could be the use of a heat wave definition that differed from that used by the National Weather Service's (NWS) heat warning system. NWS operates 122 weather forecast offices (WFOs) across the country, with each WFO responsible for a geographic area, called a county warning area, for which the WFO collects weather data and issues alerts to the public when current or forecasted weather conditions are deemed severe enough to be hazardous to human health. Warnings have been established for hazards including cold weather, excessive heat, fire weather, flooding, hurricanes, and tornadoes (US National Oceanic and Atmospheric Administration 2015).

For excessive heat, NWS has developed three products: Heat Advisory, Excessive Heat Warning, and Excessive Heat Watch. These three products utilize absolute thresholds of heat, which are selected based on estimates of the onset of heat-related illness (US National Oceanic and Atmospheric Administration 2015). Instead of defining heat waves as two or more consecutive days $\geq 90^{th}$ percentile of maximum daily heat index, future work could select those days in which WFOs for the study cities issue heat warnings to represent heat waves. WFO-issued Heat Advisories and Excessive Heat Warnings are recorded in the National Climatic Data Center's Non-Precipitation Watches, Warnings, Advisories Bulletin (bulletin ID WWUS7) and are publicly accessible through the Service Records Retention System (SRRS) Text Products/Bulletin Selection interface (Vargo, Xiao, and Liu 2015).

6.5 Conclusion

This chapter detailed Question 3, the third and final central research question of this work: How do heat waves associate with outdoor, indoor, and total physical activity behavior across all active living domains? In particular, this chapter overviewed the knowledge gap in the literature, research sub-questions and hypotheses, methods specific to these questions, output from statistical models, interpretation of results, limitations of the research design, and possible solutions to these limitations in future work. The major takeaway is that heat waves do not exhibit significant associations with outdoor, indoor, and total physical activity. The chapter did not cover the implications of this finding or recommendations for practice, which will be covered at length in the next chapter.

CHAPTER 7. RECOMMENDATIONS FROM STUDY FINDINGS

7.1 Introduction

The preceding three chapters tested the three central research questions of this study through multilevel modeling, and came to the general conclusion that extreme summer heat did not have a significant correlation with outdoor, indoor, or total physical activity for both versions of the dependent variable (i.e., Any Activity and Recommended Activity). While hot weather did not hinder (or promote) physical activity, these insignificant results may have significant consequences for public health. This final chapter addresses the potential meaning of the findings for practice, and then offers three recommendations based on these findings: 1) improve weather reporting, 2) incorporate heat risk in physical activity promotion, and 3) manage heat for physical activity. These recommendations are discussed in order of priority of implementation, with recommendations ranked by resource needs (i.e., time, financial capital, material, and labor), number of population served, and ease of implementation.

7.2 Implications of Findings

With heat predicted to not be a barrier to physical activity, individuals who are participating in physical activity in hot environments are at increased risk for heat-related health complications. Section 2.5.1 explains how an individual's core body temperature can increase in two ways: 1) performing physical activity and 2) being subjected to a hot ambient environment. Physical activity can overburden the human body's thermoregulatory centers, as heat production during intense physical activity has been measured to be 15 to 18 times greater than at rest – sufficient to raise the core body temperature of an average-sized individual by 1˚C every five minutes if without thermoregulatory adjustments (Nadel et al. 1977). Exertional heat illness (EHI), defined as heat illnesses that result from physical activity, have been reported to occur even in the absence of hot and humid conditions (Binkley et al. 2002). However, the likelihood of EHIs increases in hot, humid weather because of compounding heat stress from activity and these ambient conditions.

The findings of this work may have significant implications for public health, because physical activity needs and environmental conditions are at odds. A large proportion of adults in the US do not meet the current national physical activity guidelines, which is the driving force behind public health practitioners promoting physical activity. But the combination of 1) public health professionals motivating individuals to be physically active through promotion strategies and 2) this work suggesting extreme heat to not hinder physical activity may cause individuals to be simultaneously lowering their risk of chronic diseases and increasing their risk of EHIs. In addition, the global projections of increasing annual mean temperatures and heat waves (Section 1.1), as well as the continued population shift from rural to urban – the areas where heat islands occur – will only exacerbate the conflict between accruing the health benefits from physical activity and experiencing the health hazards of extreme heat. As such, this work provides three primary recommendations – based on the findings of this work – to safely promote physical activity in a warming climate.

While a cause-and-effect relationship between summer heat and physical activity cannot be ascertained from this work due to limitations of the research design (Sections 4.4, 5.4, and 6.4), the following three recommendations can improve city function and overall resilience – independent of the validity of study findings – by ensuring safe physical activity in hot conditions, as well as through provision of positive externalities. For example, if cities plant trees, a proven heat management strategy (Section 7.5.1), air temperatures will be reduced and thermal comfort will be improved in hot weather, whether or not hot days interact with trees to associate with physical activity. In addition, trees supply other ecosystem services that simplify the decision to add to the urban forest, such as carbon sequestration, air filtration, stormwater infiltration, food provision, noise reduction, and psychological well-being (Wolch, Byrne, and Newell 2014). Yet the chief benefit from the three proposed recommendations is that these proactive measures protect individuals from EHIs, prior to further warming and population growth in cities.

7.3 Recommendation #1: Improve Weather Reporting

Recommendation #1: Improve specificity of current and forecasted local weather conditions and heat warning systems by including physical activity component

7.3.1 Current and forecasted local weather conditions

To the tune of 115 times per month, on average, the general population makes use of weather service providers to obtain current and forecasted local weather conditions (e.g., precipitation, temperature, humidity, and wind) that may prove useful for informing near-term decision making (Lazo, Morss, and Demuth 2009). While most individuals check the weather forecast to simply know what the weather will be like, individuals also check weather forecasts for planning their daily activities (Section **Error! Reference source not found.**). The public learns of current and forecasted weather conditions from both public and private weather service providers.

The National Weather Service (NWS) is the federal agency that serves as the primary source for weather forecasting and information services, including warnings of hazardous weather, in the United States. The mission of NWS is to “provide weather, water, and climate data, forecasts and warnings for the protection of life and property and enhancement of the national economy" (US National Oceanic and Atmospheric Administration n.d.). NWS defines the current local weather based on the weather conditions at the geographically closest airport weather station to the location of interest. NWS forecasts also utilize airport weather stations, among an array of ground-based and airborne instruments, to measure weather conditions and to run weather forecast models.

Conversely, Weather Underground is a commercial weather service provider owned by The Weather Company whose mission is to "make quality weather information available to every person on this planet" (Weather Underground n.d.). Adherence to this mission statement is shown by how Weather Underground identifies current local weather, which is based on the weather conditions at the geographically closest weather station to the location of interest, whether it be any given station from almost two thousand Automated Surface Observation System stations located at airports, over 250,000 personal weather stations maintained by members of the community, or 26,000 weather stations that are part of the Meteorological Assimilation Data Ingest System. Weather Underground generates forecasts from its forecasting system, called BestForecast, which is based on an ever-expanding network of over 250,000 personal weather stations (Weather Underground n.d.).

Yet while weather service providers show current and forecasted conditions, which typically include precipitation, temperature, heat index, wind speed/direction, cloud cover, and pressure, the providers do not measure WBGT or display when physical activity would be dangerous due to heat conditions. Neither NWS or Weather Underground can calculate WBGT because American weather stations do not directly measure solar radiation, one of the four inputs for WBGT. With this work finding heat to not serve as a barrier to physical activity of adults, weather service providers should locate or develop a network of weather stations capable of measuring WBGT, in effect educating the public on the safety of the ambient environment for physical activity.

Along with adding current and forecasted WBGT values for a given area, weather service providers should share health-based heat thresholds for when ambient conditions are unsafe for physical activity. A heat threshold, computed initially using heat index and later developed using WBGT, would serve a similar purpose to that of the air quality index (AQI) developed by the US Environmental Protection Agency. In its current form, the AQI reports daily air quality for five of the six major air pollutants regulated by the Clean Air Act: carbon monoxide, ground-level ozone, nitrogen dioxide, particulate matter, and sulfur dioxide. The AQI ranges from 0 to 500, and is divided into six color-coded levels of health concern based on AQI value: good (0-50), moderate (51-100), unhealthy for sensitive groups (101-150), unhealthy (151-200), very unhealthy (201-300), and hazardous (301-500) (US Environmental Protection Agency 2016b).

With this study showing heat not to impact physical activity levels, increasing the helpfulness of weather information by displaying weather in relation to physical activity may better inform activity selection. This work recommends NWS and Weather Underground to display current and forecasted WBGT values, as well as whether these WBGT values exceed levels for modification or cancellation of physical activity for healthy adults, as outlined by the American College of Sports Medicine and to be covered in the next section (Table 18). Like the AQI, the ranges of WGBT can be divided into eight color-coded levels to aid user interpretation. The Weather Underground website does include a Wind Chill & Heat figure, but the simple scale only consists of three levels (i.e., extreme danger, OK, and extreme danger), with no publicly-available information about scale development or health outcomes.

Weather Underground allows users to access local weather conditions from anywhere with its mobile application, which has different functionality from its website. The mobile application includes Smart Forecasts, which let users "see when the weather conditions are just right for their favorite hobbies and activities" (The Weather Company 2016). Users define their acceptable and ideal ranges of weather conditions (e.g., temperature and chance of precipitation) for specific activities (e.g., running and cycling), and then Smart Forecasts provide hourly, daily, and weekly graphs that highlight when those weather conditions are met. The utility of Smart Forecasts is in its ability to assist users in decision making (i.e., when to be physically active) and by promoting physical activity, as the alerts may spur activity when ideal weather conditions are met.

But the current design of Smart Forecasts is a health hazard, as individuals could set the upper range of weather conditions at levels that put themselves at risk for exertional heat illness. This work recommends that Smart Forecasts issue a warning to users when the combination of user-defined ranges of weather conditions are unsafe for a specific activity. In addition to considering the effect of weather conditions on health, Smart Forecasts should also ask users to input other information – known to place individuals at risk for heat-related illness (e.g., preexisting medical conditions, age, weight, and physical activity intensity and length) – and then compute how the combination of these characteristics alongside set weather conditions impacts the risk of exertional heat illness. Since individuals lose confidence in forecasts with lead times of more than five days (Phan et al. 2018), the focus of Smart Forecasts should be on current, hourly, and five-day time frames.

7.3.2 Heat warning systems

NWS weather forecast offices (WFOs) issue a Heat Advisory to the public within 12 hours of dangerous heat conditions, generally defined as when daytime heat index is expected to be ≥ 100˚F in the North (or ≥ 105˚F in the South) and the nighttime air temperature remains ≥ 75˚F for one to two days. When daytime heat index is expected to be ≥ 105˚F in the North (or ≥ 110˚F in the South) and the nighttime air temperature remains ≥ 75˚F for two or more consecutive days, WFOs issue an Excessive Heat Warning to the public within 12 hours of the onset of dangerous heat conditions. When conditions are favorable for an excessive heat event in the next one to three days, but the occurrence and timing of the event are still uncertain, WFOs issue an Excessive Heat Watch (US National Oceanic and Atmospheric Administration 2015). These heat products reference the typical criteria developed by the National Weather Service for issuing products, while in practice, WFOs are encouraged to develop location-specific criteria with assistance from local health officials due to the variability in climate and effect of heat on local populations (Hawkins, Brown, and Ferrell 2017). For example, a heat index value of 105˚F feels different to residents in Florida than to residents in New York.

The NWS heat warning system is a low-cost strategy that reaches a wide spread of the population in a timely manner. The heat products have been shown to reach about 90% of the affected population, much of which is due to pervasive media coverage (Sheridan 2007). Most importantly, heat warning systems appear to be successful in safeguarding public health: Toloo et al. (2013) evaluated the effectiveness of heat warning systems, and found six studies asserting a reduction in heat-related deaths after the implementation of heat warning systems. Regarding morbidity, a study of two heat waves in Australia – only the latter of which employed a heat warning system – found that heat warning systems reduced heat-related illnesses, and that over three-fourths of the elderly recalled receiving health warnings during this second heat wave (Nitschke et al. 2016). In terms of cost-benefit, a study of Philadelphia's heat warning systems calculated $210,000 in costs compared to $468 million in benefits from saving 117 lives (Ebi et al. 2004).

Yet in its current design, the NWS heat warning system is inadequate for protecting individuals from being physically active in hot environments to the point of illness. For one, NWS heat warnings do not always exhibit agreement with the spatial variability of hazardous temperatures, as the heat index values from oftentimes a single site drive NWS heat warnings for an entire county (Vargo, Xiao, and Liu 2015). This low specificity is problematic because differences in land surface characteristics across a region impact heat index values. For instance, an airport weather station may collect lower temperatures than those found in a downtown district, an area typically defined by high amounts of dark building material, limited vegetation, heat-trapping urban form, and elevated waste heat emissions from vehicular use.

For the metropolitan areas of Atlanta, GA, and Chicago, IL, Vargo, Xiao, and Liu (2015) tested how NWS Heat Advisories and Excessive Heat Warnings, based on heat index values from a single weather station per metro, compared to heat index values from multiple weather stations (i.e., 65 stations in the Atlanta metro area and 144 stations in the Chicago metro area) that cover a far greater spatial extent of each metro. This comparison of NWS heat warnings to local weather stations exposed false positive and false negative results: NWS issued Heat Advisories and Excessive Heat Warnings for a county when such conditions were not present across the whole county, and NWS missed instances when Heat Advisories and Excessive Heat Warnings should have been issued for urbanized areas within a county.

Taking into consideration the findings that physical activity levels are not significantly impacted by heat wave events, this work proposes four enhancements to heat warning systems, which, if adopted, can bring accurate, site-specific weather information to those at risk of EHIs. First, the NWS heat warning system can improve its spatial precision to avoid misreporting heat products. False positive results waste heat response resources on non-hazardous heat conditions, while false negative results could cost lives during hazardous heat events. Secondly, this work advises NWS to post two sets of heat products: the current set defined by minimum thresholds of heat index, and a new set defined by minimum thresholds of WBGT. The rationale behind having two sets of heat products is that heat index is calculated for shaded areas, while WBGT measures heat stress in direct sunlight (US National Oceanic and Atmospheric Administration 2018b). As individuals move between shaded and sunny areas throughout the day, heat products should mention the health hazards of both. For nighttime, the NWS should only base heat products off heat index due to the lack of sunlight.

Along with performance and measurement issues with the NWS heat warning system, only about half of those who are aware of warnings modify their behavior (Sheridan 2007). One reason for this low percentage of behavior modification could be related to a lack of meaningful guidance of what specific heat-protective actions to take.

While counties rely on affiliated NWS WFOs to issue heat products, each county has its own range of different heat mitigating responses and interventions, which lack consistency and specificity in their messages on recommended behavior modification during hazardous heat episodes.

In an evaluation of heat warning systems in Dayton, OH, Philadelphia, PA, Phoenix, AZ, and Toronto, Canada, researchers asked residents in each city to recollect the specific advice given and actions taken during heat events. The study found most residents recalled the recommendation to avoid the outdoors and sun, yet only 10%, 7%, 14%, and 19% of residents in Dayton, Philadelphia, Phoenix, and Toronto, respectively, recalled the recommendation to avoid overexertion (Table 17). In terms of actions taken in response to a heat event, only 9% 12%, 11%, and 17% of residents in Dayton, Philadelphia, Phoenix, and Toronto, respectively, recalled limiting or changing activity. The small percentage of residents who remembered physical activity recommendations or limiting/changing their activity is alarming when performing physical activity is the other physiological driver, along with subjection to hot ambient environments, that elevates an individual's core body temperature.

Table 17. Evaluation of municipal heat warning systems: Percentage of respondents (n = 908) who recollected advice given and actions taken during heat events.

Source: Sheridan (2007)

	Dayton (%)	Philadelphia (%)	Phoenix (%)	Toronto (%)
RECOMMENDATIONS RECALLED				
Avoid the outdoors/sun	76	59	79	62
Keep hydrated	63	44	49	38
Stay in or seek an air-conditioned location	35	52	20	36
Utilize fans	11	28	1	0

Avoid overexertion	10	7	14	19
Dress appropriately	9	9	4	3
Check on neighbors or the elderly	2	6	1	1
Messages targeted elderly, children, sick	6	7	5	15
Cooling centers/Hotline/Other Muni activity	4	9	1	12
Didn't listen/no suggestions	9	9	12	12
ACTIONS TAKEN				
Stayed in the house	47	32	25	31
Limited or changed activity	9	12	11	17
Kept hydrated	5	5	1	3
Sought out a cooler location	0	2	1	3
Other	2	3	3	3

Within issued NWS heat products, WFOs provide a summary of precautionary/preparedness actions for each heat event, yet the included actions are narrow in scope and vary per issued product. For example, of the 12 heat products issued on July 28, 2018, NWS WFOs included direct language that advised against performing physical activity in the heat in only three of the seven Heat Advisories and one of the five Excessive Heat Warnings (US National Oceanic and Atmospheric Administration 2018d, US National Oceanic and Atmospheric Administration 2018e).

Specifically, a Heat Advisory for the Las Vegas area on July 28, 2018, advised residents to reschedule strenuous activities to morning or evening (APPENDIX G. heat advisory by US National Weather Service). Yet while morning and evening are cooler than midday, temperatures may remain hazardous during these periods. In addition, the Heat Advisory does not specify which populations are most vulnerable to heat-related illness. In another heat product on the same date, a WFO issued an Excessive Heat Warning for the San Diego area, warning against leaving young children and pets unattended in vehicles (APPENDIX H. Excessive Heat Warning by US National Weather Service). This heat product fails to not only mention the dangers of physical activity in the heat, but also omits all population groups except young children and pets from its summary of precautionary/preparedness actions.

Thirdly, this work recommends that all 122 WFOs across the United States establish heat products that include the health risks of being physically active in the heat, as well as which populations are at greatest risk of exertional heat illness. The heat products should then provide strategies to ensure safe physical activity during these hot conditions. Examples include moving physical activity indoors to climate-controlled environments, shorter bouts of outdoor physical activity, and frequent water breaks during exercise. The aforementioned risk and strategy information should be congruent across all WFOs, while each WFO should also include unique, location-specific information based on county demographics. For instance, WFOs should issue targeted messages to portions of a county that exhibit heat islands and have a large proportion of individuals at great risk for heat-related illness, such as the elderly.

Fourthly, if heat warning systems are to be truly effective in reducing heat-related morbidity and mortality, then replacing or supplementing the NWS heat warning system may be needed. Instead of countywide NWS heat warnings that are based on heat index values from usually one site, heat warnings can be issued at a finer scale (e.g., organization- or individual-level). The organization-level heat warning system need not be population-wide due to cost limitations and because individuals in certain locations (e.g., climate-controlled office buildings) are at low risk of EHIs. Instead, organizations that typically comprise individuals who are at high risk for EHIs (e.g., daycare centers, schools, outdoor gyms, athletic organizations, assisted living communities, and hospitals) should have their own on-site heat warning system that is based on WBGT values from the geographically closest Weather Underground weather station and utilizes the WGBT thresholds illustrated in Table 18 (Section 7.3.1). Each organization's on-site heat warning system can literally raise heat awareness by borrowing from the US Environmental Protection Agency's Air Quality Flag Program, in which an organization raises one of five colored flags that corresponds to the AQI for that day, with the purple flag signifying the lowest "Very Unhealthy" AQI and the green flag signifying the highest "Good" AQI (US Environmental Protection Agency n.d.). This "Heat Flag Program" could also be applied to public spaces that are conducive to physical activity (e.g., public parks), and a phone-based version could be made available to those who are at high risk for EHIs for home use.

Even with improvements to current/forecasted local weather conditions and heat warning systems, there is no guarantee that individuals will protect themselves from hazardous heat conditions during physical activity, as individuals have different probabilistic thresholds for taking protective action from given weather conditions (Morss, Lazo, and Demuth 2010). The next two recommendations are alternative avenues for safe physical activity in hot weather that take the onus off of the public to protect themselves from heat.

7.4 Recommendation #2: Incorporate Heat Risk in Physical Activity Promotion

Recommendation #2: Incorporate heat risk within physical activity interventions and assessments

7.4.1 Physical activity interventions

The intent of a public health intervention is to "promote or protect health or prevent ill health in communities or populations" (Rychetnik et al. 2002). Public health interventions differ from clinical interventions by working at the population level, not preventing or treating illness in single individuals. In physical activity interventions, public health agencies and nongovernmental organizations promote physical activity with the aim of increasing physical activity behavior in whole populations, and ultimately to prevent and manage noncommunicable chronic diseases that stem from physical inactivity. Referencing the Ecological Model of four domains of active living (Figure 2), physical activity behavior is influenced by factors operating at multiple levels, including personal, social, and environmental levels. As such, interventions that follow a holistic approach (i.e., operate at multiple levels to bring about behavior change) are found to be the most effective at modifying physical activity (Bauman et al. 2012).

Armed with the finding that extreme heat does not serve as a barrier to physical activity of adults, this study recommends that public health professionals who are administering physical activity interventions to employ strategies that ensure safe physical activity in hot and humid conditions. Ultimately, the decision for when to employ these physical activity safety strategies and for whom to employ these strategies depends on WBGT levels for physical activity set by the American College of Sports Medicine (ACSM), and the vulnerability of the intervention population to EHIs. With the purpose of reducing EHIs, the ACSM has developed physical activity guidelines, based on different WBGT levels, for modification or cancellation of workouts or athletic competition for healthy adults (Table 18).

Table 18. Physical activity guidelines, based on different wet bulb globe temperature levels, for modification or cancellation of workouts or athletic competition for healthy adults.

Source: Armstrong et al. (2007)

WBGT [b]			Training and Noncontinuous Activity	
°F	°C	Continuous Activity and Competition	Nonacclimatized, Unfit, High-Risk Individuals [c]	Acclimatized, Fit, Low-Risk Individuals [c,d]
≤50.0	≤10.0	Generally safe; EHS can occur associated with individual factors	Normal activity	Normal activity
50.1–65.0	10.1–18.3	Generally safe; EHS can occur	Normal activity	Normal activity
65.1–72.0	18.4–22.2	Risk of EHS and other heat illness begins to rise; high-risk individuals should be monitored or not compete	Increase the rest:work ratio. Monitor fluid intake.	Normal activity
72.1–78.0	22.3–25.6	Risk for all competitors is increased	Increase the rest:work ratio and decrease total duration of activity.	Normal activity. Monitor fluid intake.
78.1–82.0	25.7–27.8	Risk for unfit, nonacclimatized individuals is high	Increase the rest:work ratio; decrease intensity and total duration of activity.	Normal activity. Monitor fluid intake.
82.1–86.0	27.9–30.0	Cancel level for EHS risk	Increase the rest:work ratio to 1:1, decrease intensity and total duration of activity. Limit intense exercise. Watch at-risk individuals carefully	Plan intense or prolonged exercise with discretion[f]; watch at-risk individuals carefully
86.1–90.0	30.1–32.2		Cancel or stop practice and competition.	Limit intense exercise[f] and total daily exposure to heat and humidity; watch for early signs and symptoms
≥90.1	>32.3		Cancel exercise.	Cancel exercise uncompensable heat stress[e] exists for all athletes[f]

[a] revised from reference (38).
[b] wet bulb globe temperature.
[c] while wearing shorts, T-shirt, socks and sneakers.
[d] acclimatized to training in the heat at least 3 wk.
[e] internal heat production exceeds heat loss and core body temperature rises continuously, without a plateau.
[f] Differences of local climate and individual heat acclimatization status may allow activity at higher levels than outlined in the table, but athletes and coaches should consult with sports medicine staff and should be cautious when exceeding these limits.

Based on these physical activity guidelines with respect to WBGT, public health practitioners should 1) use a WBGT heat stress meter to measure WBGT within the location of the proposed physical activity intervention; 2) assess the level of EHI risk for the intervention population through collection of the heat acclimatization level, fitness level, health status, and biological characteristics of the intervention population; and 3) employ physical activity safety strategies if the intervention population is identified as vulnerable to EHI.

In assessing the EHI risk of a physical activity intervention, public health practitioners should evaluate the intervention population's level of heat acclimatization and physical fitness, as high levels of both reduce vulnerability to EHIs. Greater acclimatization means one's body is physiologically better equipped to cope with heat, and improvements in physical fitness increase VO_2 max (i.e., the maximum amount of oxygen that an individual can use during physical activity) (Bennett-Guerrero et al. 2017). EHI risk assessment should also include screening for population subgroups that have difficulty with thermoregulation and those with chronic diseases (Section 2.5.2), as well as those predicted by this study to be more active outdoors (i.e., males) and indoors (i.e., females), on average (Table 6, Table 7, Table 11, Table 14, Table 15).

With this study finding that heat does not have a significant impact on outdoor, indoor, or total physical activity levels of adults, public health practitioners administering physical activity interventions should heed the following additional recommendations. In accordance with guidelines for outdoor workers from the US Centers for Disease Control and Prevention, physical activity interventions should encourage medium-term acclimatization (i.e., 8-14 days of acclimatization) and an acclimatization schedule: New workers should have no more than a 20% exposure on day one and an increase of no more than 20% on each subsequent day, while experienced workers should have no more than a 50% exposure on day one, 60% on day 2, 80% on day 3, and 100% on day 4 (US Centers for Disease Control and Prevention 2018b). Physical activity interventions can apply these acclimatization schedules by replacing the term “worker” with “physical activity participant in hot conditions.”

Interventions should also pay close attention to the amount of air conditioning used by the intervention population, as long-term exposure to air-conditioned environments may weaken an individual’s thermal adaptability (Yu et al. 2012). To fix, public health practitioners can advise intervention participants to modestly increase the temperature on their thermostats, as well as spend more time in naturally ventilated environments. As an extra benefit, any reduction in air conditioning use would reduce urban heat islands and potentially heat-related illness, as air conditioning systems expel waste heat into the surrounding environment (Section 2.5.3).

When designing physical activity interventions, public health practitioners should slowly introduce individuals to a physical activity regimen to protect from overexertion in hot and humid conditions. From use of WBGT readings in different locations of potential physical activity, practitioners can advise the intervention population of heat safe and unsafe locations for physical activity. Education initiatives on hot weather physical activity for the intervention population should include tactics for avoidance of outdoor physical activity during the hottest part of summer days, reduction of physical activity intensity and duration, breaks during physical activity, light and loose clothing to not impede heat loss, fluid replenishment to continue sweat production, and awareness of cool areas and water sources in proximity to the place of activity. Another physical activity heat safety strategy includes an exercise buddy system, whereby exercising with others in hot and humid conditions allows communication and response to EHI warning signs.

For those who are vulnerable to EHIs, public health practitioners should advise against partaking in certain activities, such as football and long-distance running, which have been shown to result in a disproportionate number of EHIs among both professional and non-professional athletes (Martin 1998, Yard et al. 2010). Individuals who have difficulty with thermoregulation should shift exercise from hot and humid outdoor settings to climate-controlled, indoor settings. In hot and humid conditions, practitioners should place added focus on physical activity of the elderly, a group who do not see themselves as vulnerable to hot weather. Males, predicted to be more physically active outdoors than females, should be closely monitored for EHIs when outside. For females, who are predicted to be more physically active indoors than males, practitioners should ensure those buildings are air-conditioned. For those with chronic diseases and/or on medications that impede thermoregulation, medical professionals should prescribe only climate-controlled, indoor settings for physical activity, or times of day when WBGT is at its lowest.

7.4.2 Health impact assessments

The US Centers for Disease Control and Prevention (2016) defines a health impact assessment (HIA) as a "process that helps evaluate the potential health effects of a plan, project, or policy before it is built or implemented." Specifically, HIAs identify the potential positive and negative public health impacts of a proposed plan, project, or policy, and then provide feasible recommendations to increase the positive health effects and decrease the negative health effects. HIAs are most often a voluntary practice and are undertaken during the decision-making process for plans, projects, and policies that are traditionally outside the public health field, including transportation and city planning (US Centers for Disease Control and Prevention 2016).

HIAs use various methods, yet most follow a linear, six-step process: 1) screening, 2) scoping, 3) assessment, 4) recommendations, 5) reporting, and 6) monitoring and evaluation. An HIA conducted from 2005-2007 on the Atlanta Beltline – a multibillion-dollar parks, trails, transit, and redevelopment project in the heart of Atlanta, GA – exemplifies this process. For screening, an interdisciplinary team of city planners, public health professionals, and physicians studied the literature, concluding that the Atlanta Beltline could significantly impact health. For scoping, the team identified potential positive and negative health impacts of the project by reviewing the literature, understanding local demographic and health data, and evaluating stakeholder concerns through outreach events and a survey. For assessment, the team prioritized and then selected assessment topics based on data gathered while scoping, resulting in five topics: access and social equity, physical activity, safety, social capital, and environmental quality. (Ross et al. 2012).

With public health assessment topics identified, the HIA team obtained health data from local sources and conducted analyses to arrive at 72 specific recommendations to increase beneficial impacts and decrease harmful impacts of the Atlanta Beltline on public health. The team shared the 232-page HIA report at public meetings and Beltline planning meetings, as well as with government officials. Lastly, the HIA team continues correspondence with decision makers to monitor and evaluate the implementation and impacts of the 72 recommendations over the project's 25-year implementation time period (Ross et al. 2012).

While widely applied in Europe and gaining popularity in the US, HIAs are still not typically conducted on most major US plans, projects, or policies (Collins and Koplan 2009, Dannenberg et al. 2008). The lack of HIAs in the US, coupled with the findings that heat was not a barrier to physical activity, moves this work to recommend 1) institutionalizing HIAs in the US to inform decisionmakers who are outside the traditional public health realm, and 2) investigating whether the proposed plan, project, or policy has a link to physical activity and an impact on heat. For plans, projects, and policies that could impact those spaces where physical activity may occur, interdisciplinary HIA teams should include an urban climatologist to identify the heat profile of the affected area, and model how the plan, project, or policy impacts the WBGT. The HIA can reveal when a plan, project, or policy decreases WBGT and therefore safeguards individuals from heat-related illness in warmer months, and when a plan, project, or policy increases WBGT and which heat management strategies (Section 7.5) to employ to moderate the heat threat. Furthermore, including the health angle of heat and physical activity in HIAs could open new funding opportunities from local, regional, and federal health agencies to ensure health protection.

Both physical activity interventions and health impact assessments offer direction from a public health expert, who holds the intervention population or those in charge of the plan, project, or policy under HIA review personally accountable for adhering to recommendations. This contrasts weather forecast providers and heat warning systems, which conventionally allow the public to independently decide their own actions. Yet physical activity interventions and HIAs exclude populations that are physically active and areas of the city that fall outside the boundaries of the plan, project, or policy under review, respectively. The next and final recommendation from this work requires no behavior modification from the public and no restrictive bounding by population or item under HIA review.

7.5 Recommendation #3: Manage Heat for Physical Activity

Recommendation #3: Design urban heat management strategies through the lens of physical activity

With extreme heat leading to more deaths in the US each year than all other natural disasters combined (Luber and McGeehin 2008), and cities experiencing warmer temperatures than nearby rural areas, urban planning professionals have made concerted efforts to cool cities to protect public health. Of the four principle drivers of the UHI identified by climate scientists (Section 2.5.3), urban planners typically focus urban heat management around the drivers of loss of vegetation and high amounts of building materials.

To combat these two UHI drivers, cities primarily employ the urban heat management strategies of greening (i.e., increasing tree and other vegetative cover) and installing cool materials (i.e., using roofing and paving materials that do not warm the near-surface air temperature as much as traditional building materials) (US Environmental Protection Agency 2016c). Greening and cool material strategies are inherently place-based (i.e., biophysical and social conditions that tend to focus at local and regional scales) (Measham et al. 2011), making cities the ideal level for moderating UHIs, a phenomenon that also takes place at local and regional scales.

In recent years, cities with hazardous heat conditions have taken a detailed approach to understanding and extinguishing the hot spots within their boundaries. The cities of Louisville, KY, and Dallas, TX, two cities with some of the most rapid urban warming in the US (Stone 2007), have contracted the Urban Climate Lab at Georgia Tech to work alongside city government and local environmental organizations to develop urban heat management studies. These studies follow a stepwise process: 1) identify the locations of heat islands across a city, 2) estimate the associated heat-related mortality in these hot spots, 3) model how various urban heat management strategies impact temperatures and heat-related mortality, and 4) provide specific neighborhood-based recommendations of urban heat management strategies. The Dallas Urban Heat Island Management Study found that planting and preserving trees was 3.5 times more effective at reducing temperatures across Dallas than installing cool materials. However, Dallas had more land readily available for cool material conversions than for tree planting, and implementation of greening and cool material strategies in concert resulted in the most cooling and avoided heat-related deaths for the city (Stone, Russell, Trail, Mallen, Lanza and Vargo 2017).

Based on the findings of this study that heat has no significant impact on physical activity levels, this work recommends the continued implementation of urban heat management strategies, yet with another health outcome in mind: physical inactivity. The majority of climate scientists measure how urban heat management strategies reduce air temperature in regard to heat-related mortality (Santamouris 2014, Bowler et al. 2010, Santamouris 2013), but research does not investigate the impact of urban heat management strategies on WBGT, the temperature metric most closely linked to heat stress during physical activity. The remainder of this section explores various green and cool paving strategies, as well as less common yet effective approaches, that safeguard those being physically active on hot summer days by reducing one or more of the components of WBGT (i.e., air temperature, relative humidity, wind speed, and solar radiation). When feasible, cities should implement the described urban heat management strategies in concert and where physical activity takes place (e.g., bike paths and sidewalks) to maximize heat reductions and health benefits.

7.5.1 Greening strategies

With the aim of reducing heat stress for those participating in physical activity, planning professionals should prioritize planting urban vegetation because greening has been shown to influence components of WBGT. Regarding air temperature, cities can counteract UHIs by adding urban greenspace (i.e., vegetated areas including forest, trees, parks, allotments, or cemeteries) (Bastian, Haase, and Grunewald 2012). For instance, a 16-study meta-analysis found urban parks – a recognized setting for physical activity – to reduce temperatures by an average of 0.94˚C (Bowler et al. 2010), while Doick and Hutchings (2013) found trees, when strategically selected and placed, cooled urban areas by 2-8˚C. Trees also reduce exposure to solar radiation by shading the space below from the incoming solar radiation, protecting humans from body heat gain from the sun's energy. Because increased wind velocity increases sweat evaporation and subsequent cooling in humans, city arborists should purposefully position trees in configurations that do not serve as windbreaks (i.e., multiple rows of trees that reduce wind velocity on the other side of the vegetative barrier) (Miller and MacGowan n.d.).

While this work did not find a significant association between outdoor physical activity and either tree canopy or parks within 800m of each study participant's home, other studies have found significant positive associations between vegetation and physical activity (Janssen and Rosu 2015, McMorris et al. 2015, Villeneuve et al. 2018). For instance, Coombes, Jones, and Hillsdon (2010) found that when adults lived > 2,250m from formal greenspace (i.e., well-maintained greenspace with an organized layout and structured path network), the odds of achieving physical activity guidelines decreased by 24% ($p < 0.01$). With no studies showing a significant negative association between vegetation and physical activity, cities should support urban greening for its heat-protective properties, other proven ecosystem services, and potential to increase physical activity levels. Moreover, tree planting is a cost-effective strategy for cities, as McPherson et al. (2005) found the annual benefits ($31-89) of street and park trees in five US cities outweighed the costs ($16-35). The remainder of this section overviews city- and state-level greening initiatives that bring vegetative protection and enhancement to urban areas, with specific attention on two strategies: tree planting and greenspace planning.

In pursuit of a net increase in tree cover, cities should safeguard existing tree cover by enacting a city-wide tree protection ordinance. For example, the tree protection ordinance for the City of Atlanta calls for no net loss of trees within city boundaries. This tree protection ordinance applies to all trees on public property, and all pine trees at least 12 inches in diameter at breast height (DBH) and all other trees at least six inches in DBH on private property. In instances where tree replacement is not feasible or does not fully account for the value of the removed tree, the city collects monetary compensation from the property owner to recoup the lost public value from the removal of the healthy tree. This money is deposited in a Tree Trust Fund, which goes towards planting additional trees throughout the city. The ordinance includes the following recompense formula (Equation 9) (City of Atlanta 2010):

$$\begin{aligned} recompense &= value\ of\ trees\ removed \\ &\quad - value\ of\ trees\ replaced \end{aligned} \qquad \text{(Equation 9)}$$

The value of removed trees and replaced trees are calculated by the following formulas (Equations 10, 11):

$$
\begin{aligned}
&\mathit{value\ of\ trees\ removed} \\
&\qquad = (\mathit{number\ of\ trees\ removed} \times \$100) \\
&\qquad + (\mathit{DBH\ inches\ removed} \times \$30)
\end{aligned}
\qquad \text{(Equation 10)}
$$

$$
\begin{aligned}
&\mathit{value\ of\ trees\ replaced} \\
&\qquad = (\mathit{number\ of\ trees\ replaced} \times \$100) \\
&\qquad + (\mathit{DBH\ inches\ replaced} \times \$30)
\end{aligned}
\qquad \text{(Equation 11)}
$$

The equations include both the number and size of trees, as an increase in both these conditions increases tree value in terms of ecosystem and economic benefits. Stephenson et al. (2014) found the rate of tree carbon accumulation increases continuously with tree size, while Wolf (2007) found home price increases were associated with mature yard trees, i.e., trees with greater than nine-inch diameter-at-breast-height (2% increase), good tree cover in a neighborhood (6-9% increase), and mature trees in high-income neighborhoods (10-15%).

As a means of increasing the quantity and quality of trees in the urban forest and in effect reducing EHIs, cities can improve the tree protection ordinance for the City of Atlanta in three ways. First, the dollar amount could be increased within the formula, e.g., doubling the multiplier for number of trees to \$200 and for DBH to \$60. For those instances when property owners must pay recompense, this doubling would lead to more funds to plant trees in other locations. Second, the ordinance could lower the minimum threshold DBH for pine trees and deciduous trees on private property from 12 inches and six inches, e.g., to six inches and three inches. This halving of the DBH would increase the number of trees needing permits for removal, therefore increasing protection for younger trees to reach maturity. Lastly, instead of no net loss of trees within the city boundaries, the ordinance could require a net increase in trees, e.g., for every tree removed, at least two trees of equal DBH to the tree removed shall be planted in its place. A limitation of a tree protection ordinance could be policing to make sure the policy is followed, and Tree Trust Funds are apportioned to planting more trees. To ensure adherence, cities could hire "Tree Wardens," a position held in each city in Vermont that controls the care and removal of trees on public and private property (City of Vermont 2016).

Beyond tree protection, cities could take notes from Seattle, Washington, on how to incorporate trees and greenspace into all development types via the municipal zoning code. Seattle abides by the Green Factor, a score-based zoning code requirement with the goal of increasing the quantity and quality of urban landscaping. Each zoning class (e.g., commercial, multifamily residential, and mixed-use) is required to reach a minimum Green Factor score; the property owner can select from several supplied options to reach or surpass this minimum score (Figure 16). Eligible strategies for Green Factor include plant and tree installation, green roofing, permeable pavement, rain gardens, and food cultivation (City of Seattle 2016).

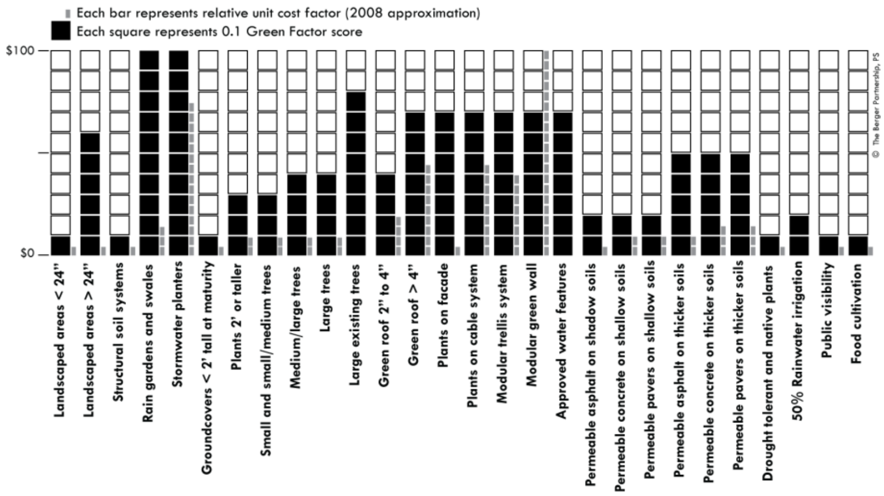

Figure 16. Green Factor's menu of options for property owners.

Source: City of Seattle (2016)

The Green Factor score mitigates UHIs across Seattle, yet the greening occurs on private property, which restricts individuals from directly participating in physical activity on these greenspaces unless the property is their own. However, vegetative cooling traverses property lines, allowing non-property owners to reap the cooling benefits from private property. For example, tree canopy oftentimes overlaps public sidewalks, providing the public with free and legal access to tree shade. The Green Factor should incentivize planting large, deciduous trees that overlap sidewalks, so as to provide a service that benefits the community and reduces the burden of the city and non-profit organizations to plant street trees.

Of the 28 supplied options to reach the minimum required Green Factor score, only four, or 14%, of the options focus on trees, i.e., small and small/medium trees, medium/large trees, large trees, and large existing trees. To encourage tree planting, the Green Factor score for non-tree options could be lowered and the Green Factor score for tree planting could be raised. In addition, the Green Factor could add “small existing trees” and “medium existing trees” as two options, which may move owners to save immature trees within their property.

To increase tree cover on public land, such as along sidewalks and within parks (i.e., areas where physical activity commonly occur), and on private property, cities can undertake citywide planting initiatives. For example, two US cities took on the momentous task of planting one million trees within their city boundaries: New York City and Los Angeles. In New York City, the Department of Parks and Recreation and the New York Restoration Project formed a formal public-private partnership to lead MillionTreesNYC, with the goal of planting and caring for one million trees by 2017. The leaders created an advisory committee that engaged over 100 environmental organizations to raise awareness (Campbell 2014). Thanks to the partnerships, public support, and volunteer tree planting, New York City reached its goal of one million trees two years ahead of schedule (MillionTreesNYC 2015).

Before the City of Los Angeles began its MillionTreesLA campaign, the city had 21% existing tree cover, ranging from 7-37% by council district. In terms of public health, McPherson et al. (2011) calculated that the potential benefits of this one million tree initiative over a 35-year period would range from $1.33-1.95 billion. Although Los Angeles has yet to reach its goal of one million trees, the tree plantings show high success in terms of tree survival, growth, and performance (McPherson 2014).

Cities could undertake a Million Trees initiative by borrowing from the successful public-private partnership framework used by New York City. A city can plant and care for one million trees within its boundaries by forming a team between the Department of Parks and Recreation and a tree planting organization, along with other supportive local partners. Regarding the cost of this city-level initiative, Peper et al. (2007) found the purchasing, planting, and maintenance of each urban tree in New York City had an average annual cost of $37, but the yearly benefits of trees exceed the yearly costs by a factor of 1.4-3.1 (McPherson et al. 2005).

A final city-level vegetative strategy is the greening of vacant properties, which has been successfully implemented in New Orleans, Louisiana. The New Orleans Redevelopment Authority (NORA), headquartered within Central City, LA, owns 2,500 vacant properties across New Orleans. These properties have been adjudicated, meaning the owners failed to pay property taxes and the city puts the property on sale. NORA cares for the properties (e.g., yardwork) to encourage new investment. Often, NORA goes beyond simple property maintenance by providing green infrastructure for stormwater management (e.g., trees and rain gardens). NORA encourages community use by installing benches, birdhouses, and fences on these properties. Through its Growing Green Program, NORA leases lots to individuals and community organizations for community gardens (New Orleans Redevelopment Authority 2016).

The greening of vacant properties by NORA can be adopted by other US cities and adapted to include physical activity infrastructure. Community gardens offer an opportunity for physical activity, as well as social engagement with other community members. For physical activity interventions, public health professionals can encourage youth to use these vegetated vacant lots for neighborhood play, and can assure parents that the lot's proximity to the home increases safety. Furthermore, planting trees in areas with foreclosed homes will be a welcome form of environmental justice, as these socioeconomically disadvantaged areas commonly have less ecosystem services and more environmental hazards within their communities (Mohai and Saha 2006).

Cities should layer city-level greening strategies and adopt policies at higher political levels, because strategies do not always perfectly fit within municipal boundaries and need to be decided and implemented at a larger scale (e.g., water management systems along rivers) (Kern and Alber 2008). Furthermore, state-level policies can serve the all-important role of fostering intergovernmental coordination, which can enhance local plan compliance with general state goals (Berke, Smith, and Lyles 2012). One such state-level greening policy is Maryland's Roadside Tree Law, which protects trees along public road rights-of-way from being trimmed or removed without a permit from the state. This law, which has been in place since 1914, helps protect the millions of trees along 30,000 miles of Maryland roads. Anyone who wishes to trim or remove a roadside tree must apply for a permit through the Maryland Department of Natural Resources, and if approved, must pay a fee of $25. If the applicant would like to remove the roadside tree, then he or she must plant a tree to make up for the removed tree; the responsibility of tree planting rests on the applicant and must be done within a year of the approved tree removal (Maryland Department of Natural Resources 2016).

One major limitation of the Roadside Tree Law is that the responsibility of tree planting after tree removal solely rests on the applicant, which may result in individuals not replacing trees due to lack of policing. Furthermore, there is no language in the law that advises on the specific location of tree planting. The law can be amended to require an arborist from the state's Department of Natural Resources (DNR) to provide an up-to-date tree map of places along roads where the applicant must plant, with suitable places defined as those of low canopy cover and potential for physical activity. The assigned DNR employee will oversee the process through the tree planting stage.

7.5.2 Cool paving strategies

Warming driven by the large amount of dark-colored, impervious building materials found in cities can be attenuated by the installation of cool materials, which are typically applied to roofs and pavement. Cool materials, especially cool paving, have significant cooling potential because impervious material is conventionally the most common urban land cover type, with 30-40% of urban land surfaces covered by dark-colored, impervious pavement (Li, Harvey, and Jones 2013). Since this work aims to cool areas that humans experience that are not climate-controlled, cool paving, rather than cool roofing, is the urban heat management strategy of choice. While cool roofing is an effective heat management strategy that reduces solar gain of buildings and ultimately air conditioning use and subsequent waste heat emissions to the outdoor environment, this strategy lacks a direct connection to places of physical activity and therefore will not be the focus of this recommendation.

Two forms of cool paving exist: reflective pavements and permeable pavements. Both forms reduce the air temperature component of WBGT, but through different mechanisms. Reflective pavements function the same as cool roofing, except at different sites: Light-colored material with high albedo and thermal emittance, which compared to traditional pavement, reflect a larger proportion of incoming solar radiation back into space, and store a smaller proportion of solar energy within the material to be later released into the near-surface air as heat. An increase in albedo and/or emittance reduces ambient air temperature as cool materials have lower heat convection intensity. For example, under peak solar conditions, Synnefa et al. (2008) found the surface temperature of a black surface with an albedo of 0.05 was about 50˚C warmer than ambient air temperatures, while the surface temperature of a white surface with an albedo of 0.8 was about 10˚C warmer than ambient air temperatures. Research from the Lawrence Berkeley National Lab estimated that increasing pavement albedo from 0.1 to 0.35 across a city could reduce air temperatures by 1˚F (Taha 1996).

Permeable pavement differs from traditional pavement by having more spaces between the material that allow air, water, and water vapor to pass through. When wet, permeable pavement allows a portion of the water to seep into the ground and recharge the water table, and another portion of the water held within the pavement structure to cool the pavement surface through evaporative cooling. The reduction of surface temperature from evaporation results in the release of less heat into the near-surface air. A seven-day experiment assessing the cooling effect of wetting a permeable asphalt pavement found wetting to reduce pavement surface temperatures by 1.2-1.6˚C, and to reduce near-surface air temperatures by 0.2-0.45˚C (Li, Harvey, and Jones 2013).

Along with cooling the surrounding air, cool paving holds much promise for its recognized co-benefits. The reduction in surface temperatures of both reflective pavement and permeable pavement results in cooler stormwater runoff, which results in a decreased risk of thermal shock to aquatic life when runoff drains into a nearby water body. Reflective pavements have improved visibility at night, increasing user safety and decreasing night lighting costs. Permeable pavements can reduce the amount of stormwater runoff by up to

90%, which means less surface pollutants, such as oil and fertilizers, are conveyed by stormwater and deposited into nearby water bodies (Ferguson et al. 2008).

A possible impediment to cool pavement installation for physical activity is cost. The approximate installation cost and estimated service life of conventional asphalt ($0.10-1.50 and 7-20 years) and concrete ($0.30-4.50 and 15-35 years) pavements are more attractive than the cost and life of reflective asphalt ($1.00-1.50 and 7-10 years), porous asphalt ($2.00-2.50 and 7-10 years), reflective concrete ($2.00-6.00 and 15-35 years), and pervious concrete ($5.00-6.25 and 15-20 years) (Ferguson et al. 2008). As a proxy for the cost of cool pavement, the cost of reflective roofing is anywhere from zero to ten cents more per square foot than the cost of traditional roofing (US Environmental Protection Agency 2016d). Yet the relatively high upfront investment and short lifespan of cool pavement can oftentimes be offset by the multiple benefits offered by cool pavement.

While cool pavements have been identified as a proven method to decrease surface temperatures and ambient air temperatures, one major limitation of cool paving as a technique to manage heat for physical activity is its impact on individuals located on or near the material: Cool pavements reflect more solar radiation than traditional surfaces, and this reflected energy is then absorbed by surrounding surfaces. If an individual is on or near cool pavement, then he or she absorbs that reflected radiation and consequently experiences heat gain. For example, Lynn et al. (2009) found that at noon (i.e., peak sun conditions), an increase in the albedo of an impervious surface from 0.15 to 0.50 cooled surface temperatures and consequently reduced the emittance of heat into the near-surface air; however, the amount of solar energy reflected on the person more than tripled, leading to a net gain of energy on the person of almost 80 W/m^2. Ultimately, this albedo enhancement increased temperatures experienced by individuals on the pavement by three to six degrees Celsius.

With cool paving is in its infancy compared to greening strategies and cool roofing, some projects – to be outlined later in this section – have moved forward with installing reflective pavement in activity spaces, a potential health concern because the reductions in UHI intensity from albedo enhancement may not compensate for the increase of thermal stress on the users of that space (Yang, Wang, and Kaloush 2013). This work recommends that cities install cool materials on urban surfaces that are not primarily utilized for physical activity (e.g., roads and parking lots) to reduce UHI intensity and not subject individuals to reflected solar radiation, and implement greening strategies at those locations where individuals are partaking in physical activity, such as on and around physical activity infrastructure (e.g., sidewalks, bike lanes, and sports facilities). To inform their own cool paving investments, cities can reference the following cool paving initiatives.

As the most populous city in the 2nd most populous state in the US, Houston, Texas, is characterized by the main drivers of the UHI (Section 2.5.3), resulting in urban temperatures 6-8˚F warmer than adjacent rural areas. In 2004, the City of Houston responded to the heat by contracting the Houston Advanced Research Center to develop the Cool Houston Plan, a strategic plan for urban heat island mitigation for the eight-county Houston region through public-private partnerships. The comprehensive plan serves as a resource for urban heat management strategies, and provides guidelines for the implementation of cool paving, cool roofing, and tree planting to reduce temperatures and improve air quality, water quality, and quality of life in the Houston region over a 10-year period (Houston Advanced Research Center 2004).

With pavement constituting approximately 384mi^2 (i.e., 28%) of the Houston region, the Cool Houston Plan emphasizes cool paving of three target surfaces: new parking lots, parking lot resurfacing, and new streets in residential and commercial areas (Houston Advanced Research Center 2004). Although plan developers selected these target surfaces based on having the greatest opportunity (i.e., area) for changing paved surfaces, these surfaces also fall in line with our recommendation to install cool paving where physical activity is not the principal use.

For additional temperature reduction, the City of Houston could pass policies to replace parking lots, which account for 56% of all paved surfaces in the Houston region (Rose, Akbari, and Taha 2003), with both cooler surface materials and more beneficial land uses (e.g., shops, water features, and parks). For example, the City of Dallas – the third most populous city in Texas – acquired a 3.2-acre surface parking lot in downtown, and the nonprofit organization called Parks for Downtown Dallas is transforming this one-dimensional parking lot into Pacific Plaza Park, a multifunctional public space slated for completion in 2019 (Parks for Downtown Dallas 2018). In addition to reducing temperatures and serving as physical activity space, urban parks bring mental health benefits, social cohesion, tourism, higher residential property values, increased biodiversity, improved air quality, and improved water management (Konijnendijk et al. 2013).

If the transformation from paved surface to parkland is not feasible due to land use needs and/or cost, cool paving can be utilized on the paved surface. The state of California, an international leader in mitigating human-induced warming, has recognized urban heat management as law. In 2012, the state passed Assembly Bill 296 Department of

Transportation: Paving Materials, which directed the California Environmental Protection Agency (CEPA) to develop 1) a UHI index to provide each city with a quantifiable goal for UHI reduction, 2) heat reduction strategies, and 3) a standard specification for cool pavements (AB 296, Skinner 2012). Using the UHI index, CEPA identified the City of Los Angeles as having the greatest UHI intensity of any California city, with average temperatures up to 19˚F higher east of downtown during the summer (California Environmental Protection Agency 2015).

In response to the excessive heat, Los Angeles' Bureau of Street Services installed a cool pavement coating called CoolSeal on the road surface of one city block in each of the 15 city council districts. From this $190,000 pilot program, government workers found the coating reduced surface temperatures of the asphalt road by as much as 10˚F during the summer (City of Los Angeles 2018). The next steps for this pilot program should be to develop a municipal policy that calls for the use of cool paving materials in preexisting and new projects, and to identify where in the city this cooling strategy, and others mentioned throughout this section, can safeguard those places of highest WBGT.

Cities should take caution when deciding whether to install cool paving on surfaces meant for exercise because cool paving projects are a possible health detriment rather than benefit during certain warm season hours. For example, the Los Angeles Unified School District (LAUSD) partnered with the Lawrence Berkeley National Lab to form the LAUSD cool schoolyards pilot, with the aim of making schoolyards – activity spaces typically characterized by large expanses of blacktop with painted lines for games – more thermally comfortable during the warmer months of the year. In 2013, the city applied a cool pavement coating called StreetBond over the existing schoolyard blacktop at Gardena

Elementary School in Gardena, California, raising the albedo from 0.05-0.15 to 0.31-0.44 (Gilbert, Mandel, and Levinson 2016). Yet while this pilot project had good intentions and cool paving reduces temperatures of the surface and ambient air (Santamouris et al. 2012), children using the schoolyard during peak sun hours may become hotter than before the pilot. This project may still result in cooling and improved thermal comfort if school officials restrict use of the space during peak sun hours and include other heat management strategies alongside the cool pavement coating.

Recreational and professional athletes alike are vulnerable to EHIs, and some sport surfaces, such as tennis courts and running tracks, reach higher temperatures than others. In tennis, the most common surface type is hardcourt, composed of an asphalt or concrete foundation and acrylic surface. Hardcourts have been known to reach hazardous temperature levels for their users, as illustrated by the 2015 US Open in New York. One of four major tournaments for professional tennis players, the US Open takes place at the end of summer every year, which puts invited professional athletes at great risk for EHIs. In 2015, the US Open experienced high humidity levels and temperatures of 33˚C (91˚F), which resulted in 12 players retiring in the first round alone, a tournament record. After temperatures reached 30˚C (86˚F), the women's draw was permitted a 10-minute break due to the heat policy of the Women's Tennis Association, while the men had no such respite from the heat due to the Association of Tennis Players not drafting a heat policy (The Guardian 2015).

Similar to the strategy for cooling schoolyards, a company called Astec Paints sells a highly reflective coating for hardcourts called Cool Pave, which scores 113.89 on Solar Reflective Index (SRI), a measure calculated from the solar reflectance and thermal emittance of a material, with an SRI of 0 equating to a standard black surface and an SRI of 100 equating to a standard white surface (Astec Paints 2015, US Green Building Council 2018). But if outdoor tennis matches take place during peak sun hours, the players will gain heat from both incoming and outgoing solar radiation. Instead of coating the courts, tournament organizers could safeguard tennis players from EHIs by 1) mandating that players take intermittent breaks, replace lost fluids, and wear reflective, loose-fitting clothing during matches; and 2) scheduling summer matches during cooler hours of the day or indoors during peak sun hours. A positive externality of these recommendations is that an increase in thermal comfort may increase the level of athletic performance (Section **Error! Reference source not found.**), an outcome that the players, tournament organizers, and fans can all appreciate.

7.5.3 Alternative strategies

While greening and cool material strategies are the most commonly applied for managing urban heat, cities have also showcased effective alternative strategies. One such strategy relies on constructing outdoor shade. In the natural world, humans can escape warming from direct solar radiation gain by seeking out shade from vertical objects (e.g., trees and boulders) and topography (e.g., hills and caves). Humans can also escape direct solar radiation gain by seeking manmade shelter, such as buildings, awnings, and outdoor roofed structures (e.g., gazebos). Brickell, the financial district of Miami, Florida, that consists of multi-story luxury condos and office towers overlooking Biscayne Bay, is also home to the Climate Ribbon, an architectural wonder that provides more than shade.

As part of Brickell City Center, a $1.05 billion, mixed-use project renowned for its open-air mall, the Climate Ribbon – touted as a functional art piece – is an open steel and glass structural canopy that directly covers the public spaces between the sea of retail shops. Architects designed the aesthetic Climate Ribbon for three main functions: 1) shelter shoppers from precipitation, 2) protect shoppers from the sun, and 3) provide shoppers with a breeze path. The design team ran model-based quantitative and qualitative simulations to ensure the structure met each function and resulted in optimal comfort conditions. The primary structure consists of transparent surfaces inclined towards each other that offer rain protection and convey water to a cistern for irrigation use. The structure reduces temperatures by an average of 7˚F by providing shade from the direct sun, while also maintaining desirable indirect natural lighting and views of the sky. Furthermore, the design team modeled sun-shading using the hottest periods of the day and year: midday and evening sun during the summer. To offer cooling breezes to the shoppers below, the blade elements of the structure conduct the summer trade winds from Biscayne Bay through the public spaces at 300 kilometers per hour (Stimpfle and Schäffer 2016, Financial Times 2018, Hugh Dutton Associates 2018).

All three functions of the Climate Ribbon affect human comfort and therefore movement within the spaces below. This work and the literature have shown rain to exhibit a significant negative association with outdoor physical activity, while the engineered sun shading and wind channeling directly impact thermal comfort by influencing two elements of WBGT (i.e., solar radiation and wind speed). With a cost of $30 million (Financial Times 2018), the Climate Ribbon is not practical for widespread application, but commercial centers across the US can adopt parts of the Climate Ribbon model to encourage both shopping activity and physical activity.

Like Miami, Masdar City is another city that has employed strategies to improve human thermal comfort by reducing WBGT. Situated near Abu Dhabi International Airport in the United Arab Emirates, Masdar City is a planned eco-city project that had the lofty goal of becoming the world's first zero-carbon city. Abu Dhabi envisioned Masdar City as an international cleantech knowledge and business hub, with a centrally located Masdar Institute of Science and Technology serving as the innovation machine. With construction underway since 2008, the 6km^2 project expected to house 50,000 residents has been estimated to cost US $22 billion (Caprotti and Romanowicz 2013).

For this work, the takeaway from Masdar City is that modern updates to ancient Arabic techniques have cooled the city – located in the scorching Arabian desert – by 15-20°C (Foster + Partners 2018). Climatic architectural design features in the city include buildings with self-shading facades and the use of a central 148ft wind tower, a 148ft hollow cylinder that channels winds through intentionally-designed narrow streets. The wind tower works by using louvres at the top of the tower to "catch" strong prevailing winds above the tower, and then by funneling that wind through the tower and out into the courtyards and streets below. Furthermore, the top of the tower has misters that spray water to cool the captured wind (Caprotti and Romanowicz 2013). With projected global warming and heat islands, US cities should learn from Masdar City, a place where heat management strategies are essentially compulsory because of average temperatures above 100˚F for each warm season month (US National Oceanic and Atmospheric Administration 2018c).

Bringing together the greening, cooling, and alternative strategies covered in this section, this work recommends cities create what can be called "Cool Corridors" in which a network spanning outdoors and indoors provides opportunity for physical activity while simultaneously protecting individuals from EHIs through a layering of urban heat management strategies. Regarding feasibility, much of the network foundation has already been completed: Public spaces where physical activity commonly occurs can serve as network nodes (e.g., parks, swimming pools, and gyms) and linear connectors (e.g., sidewalks, bike lanes, and trails).

After taking inventory of network nodes and connectors, cities will then conduct a spatial assessment to identify gaps in the Cool Corridor across the city, followed by an implementation plan to remediate these gaps in physical activity infrastructure. The second part of the spatial assessment will evaluate the UHIs within the Cool Corridor, and then program different urban heat management strategies at these hot spots, prioritizing those hot spots with high-risk populations for physical inactivity and heat-related illness. As a final step, cities must promote their Cool Corridors using an array of techniques (e.g., signage, information and communication technologies, and physical activity interventions), because raising general awareness will potentially promote safe physical activity, reduce automobile dependency, and bring economic gains to businesses along the Cool Corridor.

In summation, urban heat management strategies (i.e., greening, cool paving, and alternative strategies) offer promise for community-wide physical activity that is safe from heat, the weather condition predicted to not significantly impact physical activity in this study. Urban heat management is not constrained by individual behavior or specific populations, plans, projects, or policies like the other two recommendations of this work, but is limited by resource costs and political will. Concurrent implementation of all three recommendations may produce synergistic effects: Mindfulness of hazardous temperature conditions coupled with thermally comfortable spaces may produce a safer, more resilient community.

7.6 Conclusion

This chapter outlined three general recommendations (i.e., improve weather reporting, incorporate heat risk in physical activity promotion, and manage heat for physical activity) that stem from the principle takeaway of this work: Extreme summer heat may not serve as a barrier to physical activity of adults, and therefore adults being physically active in urban areas may be at increased risk for EHIs. These recommendations are feasible to implement in cities across the US, as the strategies referenced in this section originated from past or ongoing US projects.

The combination of the US physical inactivity crisis and projected continued warming from greenhouse gas emissions and development place cities in a precarious position: public health practitioners are encouraging population-wide physical activity, yet another camp of health professionals and urban climatologists have understood the morbidity and mortality risks of being subjected to hot conditions. When conducting health impact assessments and interventions for physical activity, cities should plan for the future urban climate to safely modify health behaviors.

The environments where individuals live have a profound influence on health and wellbeing, and strategies that make the healthy choice the easy choice can promote health behaviors at the community level. For physical activity, strategy design should not only consider physical activity promotion, but also heat safety. A multipronged approach that employs the three recommendations in concert could lead to a new active urban society, in which individuals are warned in advance of hazardous heat conditions, and supplied with environments both conducive to physical activity and protective from extreme heat.

APPENDIX A. TIME ACTIVITY DIARY LEGEND

Time of Day	Location Codes	Activity Level Codes	Cooling Method Codes	Thermal Sensation Codes
	Indoor 1 = home 2 = friend's or relative's home 3 = indoor workplace 4 = store/grocery 5 = bar/restaurant 6 = office (e.g., doctor, etc.) 7 = library 8 = school/college 9 = senior or rec center 10 = gym 11 = child's school/daycare 12 = movie theater 13 = cooling center 14 = church/house of worship **Outdoor** 15 = sidewalk/walking 16 = car 17 = bus/train 18 = bike 19 = motorcycle/scooter 20 = outdoor workplace 21 = yard 22 = parking lot 23 = park/athletic field 24 = pool/beach/splash pad **30 = traveled outside the city** **31 = traveled outside the metro area**	1 = sitting or lying down 2 = light exertion (breathing easy) 3 = moderate exertion (breathing harder) 4 = heavy exertion (can't have conversation)	**0 = none** **Indoor** 1 = air conditioning 2 = window/ ceiling fan 3 = open windows 4 = go to basement 5 = cool shower/ bath **Outdoor** 6 = go in the shade 7 = mister/ sprinkler 8 = swimming **Any Location** 9 = remove/ change clothes 10= drink cool beverage 11 = cool skin with water or compress	-4 = very cold -3 = cold -2 = cool -1 = slightly cool 0 = neutral 1 = slightly warm 2 = warm 3 = hot 4 = very hot

APPENDIX B. LOCATION CLASSIFICATION FOR TIME ACTIVITY DIARIES

Location	City of Record
INDOOR	
air-conditioned room	PHX
antique mall	PHX
bank	PHX
bar/restaurant	ATL, DET, PHX
casino	DET
child's school/daycare	ATL
choir rehearsal space	PHX
church/house of worship	ATL, DET, PHX
concert venue	ATL
cooling center	ATL, DET, PHX
friend's or relative's home	ATL, DET, PHX
garage	PHX
gym	ATL, PHX
home	ATL, DET, PHX
indoor workplace	ATL, DET, PHX
library	ATL, DET, PHX
movie theater	ATL, DET, PHX
museum	ATL, DET
office (e.g., doctor)	ATL, DET, PHX
other indoor	DET
Pilates class	PHX
school/college	ATL, DET, PHX
senior or recreation center	ATL, DET, PHX
shopping mall	PHX
sports arena	ATL
storage facility	PHX
store	ATL, DET, PHX
OUTDOOR	
bike	ATL, DET, PHX
deck	ATL
golf course	PHX
motorcycle/scooter	ATL
nature trail/water	ATL
other outdoor	ATL, DET, PHX
outdoor running track	ATL
outdoor workplace	PHX
park	ATL, DET, PHX
parking lot	ATL, DET, PHX
patio	PHX
pool/beach/splash pad	ATL, PHX
porch	ATL
restaurant porch	ATL
sidewalk	ATL, DET, PHX
street	ATL
tennis court	PHX
yard	ATL, DET, PHX

OTHER	
bus/train	ATL, DET, PHX
car	ATL, DET, PHX
gas station	PHX
not available	DET, PHX
other indoor/outdoor	DET
store/yard	PHX
traveled outside the city	ATL, DET
traveled outside the metro area	ATL, DET
various errands	PHX

APPENDIX C. DESCRIPTIVE STATISTICS PER CITY

C.1 Atlanta

Variable	Count	% of Total	Mean	Standard Deviation
Level 1 Time-Varying Variables[1]				
PHYSICAL ACTIVITY				
Any activity, outdoor (%)			6.8	9.4
Any activity, indoor (%)			38.1	27.1
Any activity, total (%)			44.9	27.8
Recommended activity, outdoor (%)			3.4	7.2
Recommended activity, indoor (%)			5.4	12.0
Recommended activity, total (%)			8.9	14.3
WEATHER				
Heat index (°F)			98.6	2.7
Hot day	221	70.4		
Heat wave day 2	36	11.5		
Heat wave day 3+	147	46.8		
Rainy day	100	31.8		
TIME				
Weekend day	80	25.5		
Level 2 Time-Invariant Variables[2]				
INDIVIDUAL				
Sex (female)	31	56.4		
Race (Non-White)	25	45.5		
Age (years)			44.3	16.6
Health (not good health)	14	25.5		
Income ($)			79,787	71,854
ENVIRONMENT				
Density (mean block size, acres)[3]			23.8	31.0
Safety (neighborhood unsafe)	3	5.5		
Trees (% canopy)[3]			42.9	14.1
Hilliness (mean slope, degrees)[3]			4.8	0.8
Connectivity (# road intersections)[3]			243.2	112.1
Access to parks (acres)[3]			23.8	31.0
Access to shops + services (# comm.)[3]			127.1	119.6

[1]Based on 314 days from dependent variable Any Activity (i.e., physical activity defined as intensity levels 2-4). Dependent variable Recommended Activity (i.e., physical activity defined as intensity levels 3-4) removes one Atlanta study day.

[2]Based on 55 individuals from dependent variable Any Activity (i.e., physical activity defined as intensity levels 2-4). Dependent variable Recommended Activity (i.e., physical activity defined as intensity levels 3-4) removes five Atlanta study individuals.

[3]Within 800m of each study participant's home address.

C.2 Detroit

Variable	Count	% of Total	Mean	Standard Deviation
Level 1 Time-Varying Variables[1]				
PHYSICAL ACTIVITY				
Any activity, outdoor (%)			7.8	13.0
Any activity, indoor (%)			44.0	29.0
Any activity, total (%)			51.9	28.5
Recommended activity, outdoor (%)			3.9	9.9
Recommended activity, indoor (%)			12.2	18.9
Recommended activity, total (%)			16.0	20.8
WEATHER				
Heat index (°F)			87.6	7.5
Hot day	76	28.1		
Heat wave day 2	38	14.1		
Heat wave day 3+	4	1.5		
Rainy day	79	29.3		
TIME				
Weekend day	54	20.0		
Level 2 Time-Invariant Variables[2]				
INDIVIDUAL				
Sex (female)	39	90.7		
Race (Non-White)	35	81.4		
Age (years)			43.9	15.9
Health (not good health)	17	39.5		
Income ($)			25,555	21,440
ENVIRONMENT				
Density (mean block size, acres)[3]			11.8	9.3
Safety (neighborhood unsafe)	5	11.6		
Trees (% canopy)[3]			15.6	4.6
Hilliness (mean slope, degrees)[3]			0.3	0.2
Connectivity (# road intersections)[3]			221.3	61.6
Access to parks (acres)[3]			36.5	54.6
Access to shops + services (# comm.)[3]			141.0	66.6

[1]Based on 270 days from dependent variable Any Activity (i.e., physical activity defined as intensity levels 2-4). Dependent variable Recommended Activity (i.e., physical activity defined as intensity levels 3-4) adds seven Detroit study days.

[2]Based on 43 individuals from dependent variable Any Activity (i.e., physical activity defined as intensity levels 2-4). Dependent variable Recommended Activity (i.e., physical activity defined as intensity levels 3-4) removes three Detroit study individuals.

[3]Within 800m of each study participant's home address.

C.3 Phoenix

Variable	Count	% of Total	Mean	Standard Deviation
Level 1 Time-Varying Variables[1]				
PHYSICAL ACTIVITY				
Any activity, outdoor (%)			4.8	10.0
Any activity, indoor (%)			40.6	28.1
Any activity, total (%)			45.4	27.3
Recommended activity, outdoor (%)			3.6	9.2
Recommended activity, indoor (%)			5.4	12.4
Recommended activity, total (%)			9.0	14.5
WEATHER				
Heat index (°F)			104.1	5.1
Hot day	25	15.9		
Heat wave day 2	0	0.0		
Heat wave day 3+	0	0.0		
Rainy day	24	15.3		
TIME				
Weekend day	44	28.0		
Level 2 Time-Invariant Variables[2]				
INDIVIDUAL				
Sex (female)	17	47.2		
Race (Non-White)	10	27.8		
Age (years)			47.6	18.1
Health (not good health)	4	11.1		
Income ($)			88,125	45,821
ENVIRONMENT				
Density (mean block size, acres)[3]			19.6	23.0
Safety (neighborhood unsafe)	2	5.6		
Trees (% canopy)[3]			9.8	4.1
Hilliness (mean slope, degrees)[3]			1.0	1.6
Connectivity (# road intersections)[3]			220.8	40.1
Access to parks (acres)[3]			9.2	17.1
Access to shops + services (# comm.)[3]			144.2	80.0

[1]Based on 157 days from dependent variable Any Activity (i.e., physical activity defined as intensity levels 2-4). Dependent variable Recommended Activity (i.e., physical activity defined as intensity levels 3-4) removes 30 Phoenix study days.

[2]Based on 36 individuals from dependent variable Any Activity (i.e., physical activity defined as intensity levels 2-4). Dependent variable Recommended Activity (i.e., physical activity defined as intensity levels 3-4) removes nine Phoenix study individuals.

[3]Within 800m of each study participant's home address.

APPENDIX D. RESULTS: HOW HOT DAYS ASSOCIATE WITH PHYSICAL ACTIVITY (RECOMMENDED ACTIVITY)

D.1 Outdoor Physical Activity

	Model 1	Model 2	Model 3
Fixed effects			
Intercept	0.75^{***}	0.77^{***}	0.93^{***}
Level 1-time-varying variables			
Weather			
Hot Day (0 = not hot day)		0.02	0.05
Rainy Day (0 = not rainy day)		-0.09	-0.12
Weekend Day (0 = not weekend day)			-0.04
Level 2-time-invariant variables			
Individual			
Sex (0 = male)			-0.28
Race (0 = White)			0.05
Age (0 = 44.9 years)[1]			-0.01
Health (0 = good health)			-0.21
Income ($)			0.01
City of Residence[2]			
Detroit (0 = not Detroit)			0.04
Phoenix (0 = not Phoenix)			0.06
Random effects			
τ_{00} (intercept)	0.42^{***}	0.42^{***}	0.41^{***}
σ^2	0.05	0.05	0.09
Model fit			
Reduction in τ_{00}		-0.19 %	1.66 %
Reduction in σ^2		-1.90 %	-74.7 %
AIC	2,059.9	2,064.9	1,657.1
BIC	2,073.6	2,078.6	1,670.1

Dependent variable: log of daily percentage of outdoor physical activity, Recommended Activity.
* p < 0.10 ** p < 0.05 *** p < 0.01

[1]Age variable was mean-centered to aid interpretability and protect against multicollinearity.

[2]Omitted category = Atlanta.

D.2 Indoor Physical Activity

	Model 1	Model 2	Model 3
Fixed effects			
Intercept	1.06***	1.05***	0.64*
Level 1-time-varying variables			
Weather			
Hot Day (0 = not hot day)		0.06	0.15
Rainy Day (0 = not rainy day)		-0.04	-0.04
Weekend Day (0 = not weekend day)			-0.04
Level 2-time-invariant variables			
Individual			
Sex (0 = male)			0.20
Race (0 = White)			0.14
Age (0 = 44.9 years)[1]			0.01
Health (0 = good health)			0.19
Income ($)			-0.01
City of Residence[2]			
Detroit (0 = not Detroit)			0.50
Phoenix (0 = not Phoenix)			0.01
Random effects			
τ_{00} (intercept)	0.61***	0.62***	0.64***
σ^2	0.15***	0.15***	0.11*
Model fit			
Reduction in τ_{00}		-0.25 %	-4.35 %
Reduction in σ^2		-1.01 %	27.3 %
AIC	2,424.4	2,429.3	1,923.6
BIC	2,438.1	2,443.0	1,936.5

Dependent variable: log of daily percentage of indoor physical activity, Recommended Activity.
* p < 0.10 ** p < 0.05 *** p < 0.01

[1]Age variable was mean-centered to aid interpretability and protect against multicollinearity.

[2]Omitted category = Atlanta.

D.3 Total Physical Activity

	Model 1	Model 2	Model 3
Fixed effects			
Intercept	12.71***	13.31***	8.19**
Level 1-time-varying variables			
Weather			
Hot Day (0 = not hot day)		-0.27	0.59
Rainy Day (0 = not rainy day)		-1.75	-1.46
Weekend Day (0 = not weekend day)			-0.21
Level 2-time-invariant variables			
Individual			
Sex (0 = male)			-1.32
Race (0 = White)			4.20
Age (0 = 44.9 years)[1]			-0.03
Health (0 = good health)			2.69
Income ($)			-0.30
City of Residence[2]			
Detroit (0 = not Detroit)			7.29**
Phoenix (0 = not Phoenix)			4.43
Random effects			
τ_{00} (intercept)	132.97***	132.59***	88.40***
σ^2	0.20***	0.21***	0.29***
Model fit			
Reduction in τ_{00}		0.29 %	33.3 %
Reduction in σ^2		-4.54 %	-41.0 %
AIC	5,908.7	5,902.0	4,605.4
BIC	5,922.5	5,915.8	4,618.4

Dependent variable: daily percentage of total physical activity, Recommended Activity.
* p < 0.10 ** p < 0.05 *** p < 0.01

[1]Age variable was mean-centered to aid interpretability and protect against multicollinearity.

[2]Omitted category = Atlanta.

APPENDIX E. RESULTS: HOW HOT DAYS INFLUENCE THE EFFECT OF BUILT ENVIRONMENT FACTORS ON OUTDOOR PHYSICAL ACTIVITY (RECOMMENDED ACTIVITY)

	Model 1	Model 2	Model 3
Fixed effects			
Intercept	0.75^{***}	1.18^{***}	2.76^{***}
Level 1-time-varying variables			
Weather			
Hot Day (0 = not hot day)		0.01	0.04
Rainy Day (0 = not rainy day)		-0.10	-0.12
Weekend Day (0 = not weekend day)			-0.04
Level 2-time-invariant variables			
Individual			
Sex (0 = male)			-0.25
Race (0 = White)			0.04
Age (0 = 44.9 years)[1]			-0.01
Health (0 = good health)			-0.21
Income ($)			-0.01
City of Residence[2]			
Detroit (0 = not Detroit)			-0.94^{*}
Phoenix (0 = not Phoenix)			-0.64
Environment			
Density (mean block size, acres)[3]		-0.01	-0.01
Safety (0 = neighborhood safe)		0.02	-0.23
Trees (% canopy)[3]		0.01	-0.01
Hilliness (mean slope, degrees)[3]		0.02	-0.15
Connectivity (# road intersections)[3]		-0.01	-0.01
Access to parks (acres)[3]		-0.01	0.01
Access to shops + services (# comm.)[3]		-0.01	-0.01
Random effects			
τ_{00} (intercept)	0.42^{***}	0.45^{***}	0.41^{***}
σ^2	0.05	0.05	0.09
Model fit			
Reduction in τ_{00}		-6.87 %	7.45 %
Reduction in σ^2		-2.89 %	-71.3 %
AIC	2,059.9	2,044.5	1,704.4
BIC	2,073.6	2,058.0	1,717.3

Dependent variable: log of daily percentage of outdoor physical activity, Recommended Activity.
* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

[1]Age variable was mean-centered to aid interpretability and protect against multicollinearity.

[2]Omitted category = Atlanta.

[3]Within 800m of each study participant's home address.

APPENDIX F. RESULTS: HOW HEAT WAVES ASSOCIATE WITH PHYSICAL ACTIVITY (RECOMMENDED ACTIVITY)

F.1 Outdoor Physical Activity

	Model 1	Model 2	Model 3
Fixed effects			
Intercept	0.75***	0.76***	0.93***
Level 1-time-varying variables			
Weather			
Heat Wave Day 2 (0 = not heat wave day 2)		-0.01	-0.05
Heat Wave Day 3+ (0 = not heat wave day 3+)		0.09	0.09
Rainy Day (0 = not rainy day)		-0.11	-0.13
Weekend Day (0 = not weekend day)			-0.04
Level 2-time-invariant variables			
Individual			
Sex (male = 0)			-0.27
Race (White = 0)			0.05
Age (0 = 44.3 years)[1]			-0.01
Health (0 = not good health)			-0.21
Income ($)			0.01
City of Residence[2]			
Detroit (0 = not Detroit)			0.06
Phoenix (0 = not Phoenix)			0.07
Random effects			
τ_{00} (intercept)	0.42***	0.42***	0.41***
σ^2	0.05	0.05	0.09
Model fit			
Reduction in τ_{00}		0.47 %	0.76 %
Reduction in σ^2		-6.31 %	-69.2 %
AIC	2,059.9	2,065.9	1,658.1
BIC	2,073.6	2,079.7	1,671.1

Dependent variable: log of daily percentage of outdoor physical activity, Recommended Activity.
* p < 0.10 ** p < 0.05 *** p < 0.01

[1]Age variable was mean-centered to aid interpretability and protect against multicollinearity.

[2]Omitted category = Atlanta.

F.2 Indoor Physical Activity

	Model 1	Model 2	Model 3
Fixed effects			
Intercept	1.06^{***}	1.12^{***}	0.81^{**}
Level 1-time-varying variables			
Weather			
Heat Wave Day 2 (0 = not heat wave day 2)		-0.21	-0.15
Heat Wave Day 3+ (0 = not heat wave day 3+)		-0.17	-0.15
Rainy Day (0 = not rainy day)		-0.01	-0.01
Weekend Day (0 = not weekend day)			-0.03
Level 2-time-invariant variables			
Individual			
Sex (male = 0)			0.19
Race (White = 0)			0.14
Age (0 = 44.3 years)[1]			0.01
Health (0 = not good health)			0.20
Income ($)			-0.01
City of Residence[2]			
Detroit (0 = not Detroit)			0.39
Phoenix (0 = not Phoenix)			-0.15
Random effects			
τ_{00} (intercept)	0.61^{***}	0.60^{***}	0.64^{***}
σ^2	0.15^{***}	0.16^{***}	0.11^{*}
Model fit			
Reduction in τ_{00}		1.71 %	-5.62 %
Reduction in σ^2		-5.55 %	28.3 %
AIC	2,424.4	2,428.2	1,924.9
BIC	2,438.1	2,441.9	1,937.8

Dependent variable: log of daily percentage of indoor physical activity, Recommended Activity.
* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

[1]Age variable was mean-centered to aid interpretability and protect against multicollinearity.

[2]Omitted category = Atlanta.

F.3 Total Physical Activity

	Model 1	Model 2	Model 3
Fixed effects			
Intercept	12.71***	13.75***	9.25**
Level 1-time-varying variables			
Weather			
Heat Wave Day 2 (0 = not heat wave day 2)		-3.11*	-2.61
Heat Wave Day 3+ (0 = not heat wave day 3+)		-1.55	-1.16
Rainy Day (0 = not rainy day)		-1.57	-1.12
Weekend Day (0 = not weekend day)			0.14
Level 2-time-invariant variables			
Individual			
Sex (male = 0)			-1.35
Race (White = 0)			4.20
Age (0 = 44.3 years)[1]			-0.03
Health (0 = not good health)			2.72
Income ($)			-0.30
City of Residence[2]			
Detroit (0 = not Detroit)			6.69*
Phoenix (0 = not Phoenix)			3.36
Random effects			
τ_{00} (intercept)	132.97***	131.81***	88.98***
σ^2	0.20***	0.22***	0.30***
Model fit			
Reduction in τ_{00}		0.87 %	32.5 %
Reduction in σ^2		-9.49 %	-37.3 %
AIC	5,908.7	5,894.9	4,599.7
BIC	5,922.5	5,908.6	4,612.7

Dependent variable: daily percentage of total physical activity, Recommended Activity.

* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

[1]Age variable was mean-centered to aid interpretability and protect against multicollinearity.

[2]Omitted category = Atlanta.

APPENDIX G. HEAT ADVISORY BY US NATIONAL WEATHER SERVICE

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URGENT - WEATHER MESSAGE
National Weather Service Las Vegas NV
529 AM PDT Sat Jul 28 2018

NVZ018-019-290300-
/O.CON.KVEF.HT.Y.0003.000000T0000Z-180729T0300Z/
Sheep Range-Spring Mountains-Red Rock Canyon-
Including The Town Of Mt Charleston and Red Rock
Canyon
529 AM PDT Sat Jul 28 2018

...HEAT ADVISORY REMAINS IN EFFECT UNTIL 8 PM PDT THIS EVENING...

* TIMING...Well above normal temperatures will persist through
  Saturday.

* TEMPERATURE...Mount Charleston 84 to 88.

* IMPACTS...A Heat Advisory means that a period of hot
  temperatures is expected. The hot temperatures will create a
  situation in which heat illnesses are possible...even in the
  mountains.

PRECAUTIONARY/PREPAREDNESS ACTIONS...

Take extra precautions if planning outdoor activities in the
Spring Mountains. When possible...reschedule strenuous activities
to early morning or evening. Know the signs and symptoms of heat
exhaustion and heat stroke. Wear light weight and loose fitting
clothing when possible and drink plenty of water.

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APPENDIX H. EXCESSIVE HEAT WARNING BY US NATIONAL WEATHER SERVICE

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URGENT - WEATHER MESSAGE
National Weather Service San Diego CA
256 AM PDT Sat Jul 28 2018

...EXCESSIVE HEAT WARNING CONTINUES FOR THE HIGH DESERTS FOR
THIS WEEKEND...

.High pressure aloft will weaken slightly for this weekend with an
increase in monsoonal moisture for Sunday.

CAZ060-282130-
/O.CON.KSGX.EH.W.0005.000000T0000Z-180730T0300Z/
Apple and Lucerne Valleys-
Including the cities of Victorville, Hesperia, and Apple Valley
256 AM PDT Sat Jul 28 2018

...EXCESSIVE HEAT WARNING REMAINS IN EFFECT UNTIL 8 PM PDT
SUNDAY...

* Temperature...High temperatures of 102 to 108 today, and 98 to
  104 Sunday.

* Impacts...Hot days combined with warm nights will increase the
  threat for heat illness.

PRECAUTIONARY/PREPAREDNESS ACTIONS...

Young children and pets should never be left unattended in
vehicles under any circumstances. This is especially true during
warm or hot weather when car interiors can reach lethal
temperatures in a matter of minutes.

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